Segmentation of Objects from Volumetric CT Data - Final Report

Version 12/14/11

Awareness and Localization of Security-Related Threats (ALERT)

A DHS Center of Excellence at Northeastern University

Boston, Massachusetts

This report was supported by the U.S. Department of Homeland Security under Task Order Number HSHQDC-10-J-00396

Contents

1 Executive Summary

The DHS Northeastern University Center of Excellence (COE) for explosives detection, mitigation and response entitled Awareness and Localization of Explosives-Related Threats (ALERT), was tasked by DHS to run a series of workshops to involve third parties in algorithm development. These workshops, of which there have been six since spring 2009, are known by their acronym, ADSA (algorithm development for security applications). The participants at the first ADSA workshop agreed that CT-based explosives detection equipment could be improved if the segmentation step of automated threat recognition (ATR) yielded features of explosives with improved precision. The improvements would be based on methods to overcome artifacts in CT images such as blurring, streaking and low-frequency shading. The participants also indicated that improved segmentation algorithms for aviation security could be developed using scans of non-threats on medical CT scanners.

ALERT, with funding from DHS, created in 2010 the segmentation initiative in which five research groups were provided scans of non-threats on medical scanners. The researchers developed segmentation algorithms and presented their algorithms at a recent symposium. The symposium also addressed the applicability of the segmentation algorithms to existing explosives detection equipment and reviewed steps for continuing their research. **The purpose of this document is to report on all aspects of the segmentation initiative. The key findings and recommendations from the workshop are as follows.**

Findings: The program has achieved its goals: Third parties developed segmentation algorithms that are useful. ALERT succeeded in engaging third parties. Third parties learned about CT-based EDS and items in bags. The program was efficient, provided five research groups in CT segmentation for minimal resources.

Recommendations: Provide additional funding to ALERT so that third parties can continue their work. Execute initiatives for reconstruction and other detection modalities.

2 Disclaimers

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This report summarizes an initiative during which a number of people participated. The views in this report are those of ALERT and do not necessarily reflect the views of all the participants. All errors and omissions are the sole responsibility of ALERT.

The material in this report is based upon work supported by the U.S. Department of Homeland Security under Order Number HSHQDC-10-J-00396. The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the U.S. Department of Homeland Security.

This final report is intended to meet the final contract deliverable. A Segmentation Monograph will be published in the near future. The technical monograph will be published by ALERT and distributed to a broader "Algorithm Development for Security Applications" (ADSA) community in the the familiar ADSA monograph format. The monograph will contain the following additional information.

a. Additional details on the generation of the image database including:
    i. Description of objects scanned
    ii. Packing manifests
    iii. Project plan for packing luggage
b. Final reports from the researchers
c. Quantitative evaluation of the algorithms supplied by the researchers
d. Additional findings and recommendations
e. Material from the symposium
    i. Invitation letter
    ii. Agenda
    iii. Instructions for researchers
    iv. Attendee list
    v. Minutes
    vi. Questionnaires
f. Additional supplement materials including the following material
    i. Request for proposal
    ii. Communications with researchers
    iii. Technical reports describing tools

    iv. Non-disclosure agreement (blank)
    v. Specification for log files
g. Miscellaneous communications and errata

3 Introduction

The Department of Homeland Security (DHS) has requirements for future scanners that include a larger number of threat categories, higher probability of detection per category, lower false alarm rates and lower operating costs. One tactic that DHS is pursuing to achieve these requirements is to create an environment where the capabilities of the traditional vendors of security systems could be augmented by the development of algorithms by third parties. A third party in this context means people and organizations other than the traditional vendors. Examples of third parties include academics, national laboratories and companies other than the traditional vendors. DHS is particularly interested in following the model used by the medical imaging industry, in which university researchers have developed numerous algorithms that have eventually been deployed in commercial medical imaging equipment[A].

This project, “Segmentation of Objects from Volumetric CT Data,” is the first phase of a multi-year strategy to stimulate research and development of advanced algorithms from volumetric CT data for the purpose of enhancing automated object of interest detection algorithms for Explosives Detection Systems (EDS) and for CT-based checked baggage scanners for the check-point. The task order awarded to Northeastern (HSHQDC-10-J-00396 dated 9/21/2010) includes the management, engineering and technical coordination of the project in accordance with the Program Statement of Work.

DHS funded ALERT and LLNL (through a separate funding vehicle) to execute the segmentation initiative. As an integral part of this initiative, five research groups were selected and subsequently funded by ALERT to develop or refine existing advanced segmentation algorithms using datasets supplied to them by ALERT. The groups were closely monitored and mentored by the ALERT/LLNL team. They presented the results of their research at a symposium held on December 8th 2011.

The purpose of this final report is to present the following aspects of the segmentation initiative.

1. Program definition
2. Dataset creation
3. Participant[B] identification
4. Algorithm development
5. Independent evaluation of the algorithms
6. Recommendations for additional work

[A] When we speak of an algorithm, we are talking about the mathematical steps. The actual implementation, usually in a general purpose computer, is beyond the scope of this work.
[B] We use the terms *participant* and *researchers* to mean the 3rd party who develops an algorithm.

4 Program Description

4.1 Overview

The purpose of the program is to provide security-like data to academic researchers and third party developers, to enhance the present segmentation state-of-the-art, and to stimulate additional communication and research in the segmentation algorithm research community.

The following steps outline the process that was used to identify project participants, fund them to develop improved segmentation algorithms and evaluate the resulting algorithms. Unless otherwise noted, the task is complete. Only the researchers final report and the program published monograph are incomplete.

1. Individuals were identified through their attendance at the ALERT Algorithm Development for Security Applications (ADSA) workshop series as likely to participate in this segmentation exercise. They received a letter with a project description soliciting their participation in the Segmentation Initiative, as well as a non-disclosure agreement (NDA).
2. The recipients of the letter may request to participate via a proposal including a completed NDA. Each of the program's three Domain Experts will select 10 Candidates[C] for a total of 30 Candidates. 12 Candidates requested participation..
3. All of these Candidates received the Qualification Dataset Group[D].
4. These 12 Candidates were told to use the project description, Qualification Dataset Group and their segmentation algorithms to segment objects (>500 Modified Hounsfield units (mHU) and ≥50mL, minimum) in the Qualification Dataset Group.
5. Those Candidates desiring to obtain the Training[E] and Validation[F] Dataset Groups and be funded for additional segmentation efforts were asked to submit to ALERT both their segmentation performance on the Qualification Dataset Group and a proposal. Funding was available to support 5 final Candidates.
6. Five final Candidates were chosen to receive segmentation research subcontracts. These five, now designated as Researchers[G] , were selected based on their submitted proposals.
7. The five Researchers were given the Training and Validation Dataset Groups. The Training Dataset Group would be used to train the Researchers' segmentation algorithms. The objects in the Training Dataset Group were identified and characterized. The five researchers were then required to segment objects (again, >500 Hounsfield units (HU) and ≥50mL, minimum) in the Validation Dataset Group.
8. Researchers were required to develop segmentation algorithms and demonstrate their performance using the Training and Validation Dataset Groups to the program's three Domain Experts, who monitored progress, provided in depth mentoring and assessed performance.

[C] Candidates
[D] Qualification Data
[E] Training Data
[F] Validation Data
[G] Researchers

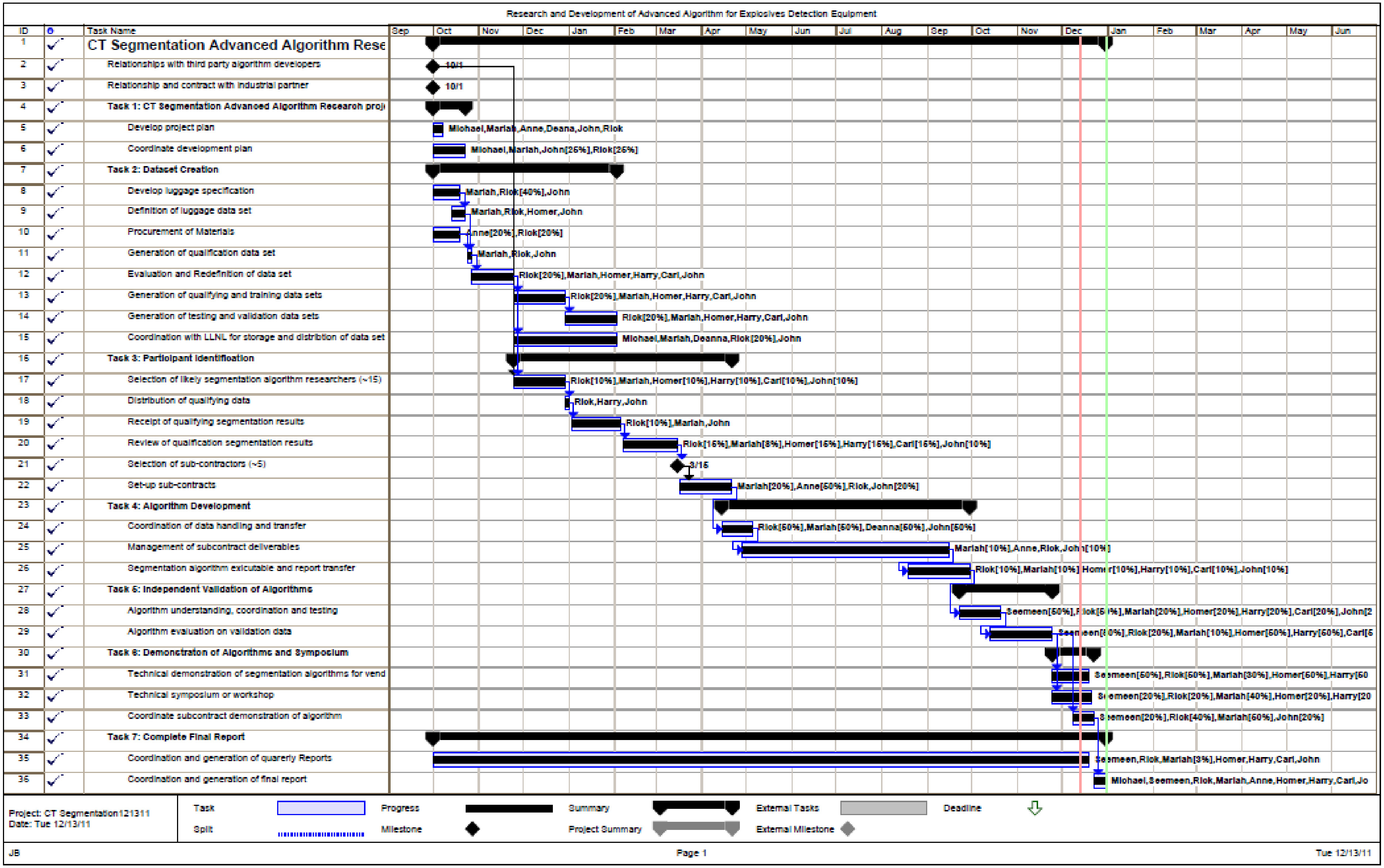
9. Each Researcher was asked to segment the objects in the Evaluation Dataset Group[H], under the superivision of the three Domain Experts to enable them to view the Researcher's process. This exercise was meant to demonstrate the ease-of-use, robustness and amount of tweaking required to obtain the segmentation results.
10. Each Researcher is required to deliver a final written report of their results from their perspective and an assessment of what could be done better performance and other improvements. **IN PROCESS**
11. The five Researchers were required to present their segmentation performance on the Training and Validation Dataset Groups to DHS and security system companies at a meeting called the segmentation symposium. At this symposium, the three Domain Experts also reviewed the five Researchers' segmentation approaches including the ease-of-use, robustness, tweaking required and performance on the Evaluation Dataset Group.
12. ALERT is required to produce a written final report on the project outcomes. This report will include the final Researcher reports as well. **IN PROCESS**

4.2 Program Gantt Chart (Schedule)

A project Gantt chart is presented in Section 4.2. It shows the program tasks, people assigned to each task, the linkages between tasks and the percent complete.

The program is on schedule with the above adjustments.

[H] Evaluation Data


Research and Development of Advanced Algorithm for Explosives Detection Equipment
ID
Task Name
Sep Oct Nov Dec Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec Jan Feb Mar Apr May Jun
1 CT Segmentation Advanced Algorithm Rese
2 Relationships with third party algorithm developers 10/1
3 Relationship and contract with industrial partner 10/1
4 Task 1: CT Segmentation Advanced Algorithm Research proj
5 Develop project plan Michael,Mariah,Anne,Deana,John,Rick
6 Coordinate development plan Michael,Mariah,John[25%],Rick[25%]
7 Task 2: Dataset Creation
8 Develop luggage specification Mariah,Rick[40%],John
9 Definition of luggage data set Mariah,Rick,Homer,John
10 Procurement of Materials Anne[20%],Rick[20%]
11 Generation of qualification data set Mariah,Rick,John
12 Evaluation and Redefinition of data set Rick[20%],Mariah,Homer,Harry,Carl,John
13 Generation of qualifying and training data sets Rick[20%],Mariah,Homer,Harry,Carl,John
14 Generation of testing and validation data sets Rick[20%],Mariah,Homer,Harry,Carl,John
15 Coordination with LLNL for storage and distribution of data set Michael,Mariah,Deanna,Rick[20%],John
16 Task 3: Participant Identification
17 Selection of likely segmentation algorithm researchers (~15) Rick[10%],Mariah,Homer[10%],Harry[10%],Carl[10%],John[10%]
18 Distribution of qualifying data Rick,Harry,John
19 Receipt of qualifying segmentation results Rick[10%],Mariah,John
20 Review of qualification segmentation results Rick[15%],Mariah[8%],Homer[15%],Harry[15%],Carl[15%],John[10%]
21 Selection of sub-contractors (~5) 3/15
22 Set-up sub-contracts Mariah[20%],Anne[50%],Rick,John[20%]
23 Task 4: Algorithm Development
24 Coordination of data handling and transfer Rick[50%],Mariah[50%],Deanna[50%],John[50%]
25 Management of subcontract deliverables Mariah[10%],Anne,Rick,John[10%]
26 Segmentation algorithm executable and report transfer Rick[10%],Mariah[10%],Homer[10%],Harry[10%],Carl[10%],John[10%]
27 Task 5: Independent Validation of Algorithms
28 Algorithm understanding, coordination and testing Seemeen[50%],Rick[50%],Mariah[20%],Homer[20%],Harry[20%],Carl[20%],John[2
29 Algorithm evaluation on validation data Seemeen[80%],Rick[20%],Mariah[10%],Homer[50%],Harry[50%],Carl[5
30 Task 6: Demonstration of Algorithms and Symposium
31 Technical demonstration of segmentation algorithms for vend Seemeen[50%],Rick[50%],Mariah[30%],Homer[50%],Harry[50
32 Technical symposium or workshop Seemeen[20%],Rick[20%],Mariah[40%],Homer[20%],Harry[20
33 Coordinate subcontract demonstration of algorithm Seemeen[20%],Rick[40%],Mariah[60%],John[20%]
34 Task 7: Complete Final Report
35 Coordination and generation of quarerly Reports Seemeen,Rick,Mariah[3%],Homer,Harry,Carl,John
36 Coordination and generation of final report Michael,Seemeen,Rick,Mariah,Anne,Homer,Harry,Carl,Jo
Project: CT Segmentation121311
Date: Tue 12/13/11
Task
Split
Progress
Milestone
Summary
Project Summary
External Tasks
External Milestone
Deadline
JB
Page 1
Tue 12/13/11

4.3 Program Expenditures

During the last two quarters of the program expenditures have accelerated. Seven invoices have been issued. They were associated with the research, data procurement, management, administration and domain expert efforts. To date, $828,131 has been charged. Most of the funds for the program have been obligated (>98%). The remaining funds will be invoiced and submitted within 90 days.

5 Program Elements and Processes

5.1 Project Definition

The following steps were taken to define the project.

1. A preliminary definition was provided by the participants at ADSA01.
2. The first version of a complete project plan was written and refined by the participants at ADSA02.
3. The project plan was revised and published as part of the final report for ADSA02.
4. A classified meeting was held with three incumbent EDS vendors to identify problem cases.
5. The project plan was converted into a task order white paper.
6. The white paper was submitted to DHS and an ALERT task order rfp was generated.
7. ALERT submitted a task order proposal to DHS which was subsequently funded. (In concert with this action LLNL made a proposal to DHS S&T and received funds to support to help implement the effort.)

5.2 Funding

The following organizations were funded as a result of the proposals that were submitted to DHS.

1. ALERT – Michael Silevitch, & John Beaty PI
2. LLNL – Harry Martz, PI

The funding for ALERT included funding for the dataset creation ($50K) and funding for five research teams ($70K each)

5.3 Database

A "Vendor" was identified and a database of CT scans of baggage and ground truth data was generated using the following steps. Page 38, provides more detail of the definition, procurement and maintenance of the four datasets.

1. A plan was written to pack suitcases with items commonly found in stream of commerce baggage. The items did not include explosives or explosive simulants.
2. Contractual arrangements were made to scan luggage on a state-of-the-art medical CT scanner at the manufacturer's factory.
3. ALERT personnel performed the following steps.
    a. Procured luggage and items to pack in them.
    b. Labeled, photographed and cataloged the items.
    c. Packed the suitcases
    d. Created a database of items as packed into suitcases
    e. Scanned the luggage at the vendor's factory
    f. Created video tapes of unpacking the luggage
4. The Vendor performed the following steps.

   a. Reconstructed the projection data corresponding to the scans of the luggage. The reconstructions were performed with offline reconstruction. The resulting resolution was approximately 3 mm FWHM.
   b. Converted the images to DICOM format.
5. ALERT then performed the following additional steps.
   a. Converted the DICOM images to TIFF files.
   b. Used a network in Mevislab to semi-automatically outline the items in the scans. The resulting data was known as ground truth data, label images and AO images.
   c. Divided the scans into four sets denoted: qualification, training, validation and evaluation.
   d. Distributed the data to the Researchers with instructions from the leadership team.
   e. Revised the data based on feedback from various stakeholders.
   f. Distributed revised data and/or offset values on a highest-priority basis to the Researchers

5.4 Researcher Proposal solicitation and selection

The following process was used to solicit proposals from prospective research groups.

1. A request for proposal was written and distributed to prospective researchers.
2. Prospective researchers were asked to submit a formal letter to receive the qualification data. An NDA had to be executed to obtain the data.
3. ALERT distributed the qualification database.
4. Prospective researchers submitted a proposal and their initial segmentation results from the qualification database.
5. The domain experts selected five research groups. These research teams (the Researchers) are listed in the following subsections.

5.4.1 Marquette University, Milwaukee, WI

Xin Feng
Taly Gilat-Schmidt
Wenjing Zhang
Jun Zhang

5.4.2 Siemens Corporate Research, Princeton, NJ

Leo Grady
Timo Kohlberger
Vivek Singh
Claus Bahlmann
Dorin Comaniciu

5.4.3 Stratovan Corp., Sacramento, CA

David Wiley
Jim Olson
Bernd Hamann

Deb Ghosh
Christian Woodhouse

5.4.4 Telesecurity Sciences Corp., Las Vegas, NV

Brandon J. Kwon
Samuel M. Song
Jason J. Lee
Douglas P. Boyd

5.4.5 University of East Anglia, UK

Paul Southam
Graham Tattersall

5.5 Algorithm Development

The five research teams developed their segmentation algorithms over a period of approximately seven months. The research teams were mentored by the domain experts during this period of time.

5.6 Symposium

A symposium was held on December 8th, 2011. The following is a list of the topics discussed during the symposium.

1. Project overview
2. Expectation management
3. Presentations from the five research groups
4. Evaluation by the domain experts
5. Recommendations for next steps

The presentations corresponding to these topics can be found in the appendices in Section 9 of this final report.

5.7 Final reports

The researchers are scheduled to deliver final reports based on their work on December 19th, 2011. A Segmentation Monograph will be created which will include the researcher's final report.

Findings and Recommendations

5.8 Researcher Performance

5.8.1 Findings

1. The Project has achieved its goals:
    a. The Five research teams:
        i. Developed and applied novel segmentation algorithms
        ii. Learned about CT-based EDS and items in bags
        iii. Learned SSI behaviors and practices
    b. ALERT learned how to:

        i. Involve third parties
        ii. Transform a classified problem into a public domain version
        iii. Learned to deal with SSI behaviors and practices

2. All of the Researchers were able to segment the objects in the dataset bags. The domain experts could quantify the specific performance results because of the following reasons:
    a. Segmentation is part of ATR, which is an integrated system geared to pass TSA EDS certification at TSL in Atlantic City by demonstrating a specific PD and PFA performance on TSA data
    b. Segmentation can also be separated from ATR to determine prevalence and features of non-threats
    c. The project Objective was only segmentation, not feature extraction and training with scans of explosives and stream of commerce data
    d. Incumbent vendors have proprietary segmentation/ATR approaches so it was impossible to compare performance against them.
3. Based on the patent literature, the Researchers created novel methods.
4. Common strengths of the five research groups:
    a. Understood problems caused by CT artifacts such as finite resolution and streaks, leading to merging and splitting of objects
    b. Implemented methods to compensate for splitting and merging
    c. Created separate algorithmic paths for some objects (e.g., sheets)
    d. Developed methods to score/evaluate results
    e. Dealt with object philosophies
    f. Have potential to solve real security problems
    g. Patents were filed or are in the process of being filed
5. Specific strengths of the research groups:
    a. Telesecurity Sciences
        i. Sequential segmentation and carving
        ii. Bilateral filtering
        iii. Recursive k-Means clustering for splitting
    b. University of East Anglia
        i. "Sieves" algorithm
        ii. Classifier strategy
    c. Stratovan
        i. Tumbler – kernel based segmentation
        ii. Automatic seed generation
    d. Marquette University
        i. Synthetic sinogram processing
        ii. Multi-path
        iii. Seed generation
        iv. Adaptive threshold
    e. Siemens Corporate Research

        i. Synthetic sinogram processing
        ii. Confidence measure
        iii. 3D display
6. Areas for improvement
    a. Feature extraction
    b. Artifact reduction in projection space
7. Areas of concern:
    a. Use of shape
    b. Turning the segmentation initiative into a classification problem
    c. Over-training on objects in the bag dataset
8. Future potential:
    a. Researchers working with vendors, DHS and TSA to enhance their algorithms and transition to fielded systems
    b. More involvement of third parties
    c. Application to AIT, AT2, and other modalities

5.8.2 Recommendations for Future Work

1. Split initiative into two projects:
    a. Segment all objects, no regard for minima
        i. Prevalence studies can be performed
        ii. Classification based on object-types
2. Support for the research community
    a. Funding
    b. Forums & conferences
    c. Databases into public domain
    d. Evaluation methodology
3. Vendors should be encouraged to compare their segmentation methods to the results of this segmentation initiative.

5.9 Database Future Development

5.9.1 Findings

1. Some of the values of the tags in the TIFF files were incorrect. (Wrong byte order used when saving some of the TIFF Images resulted in incorrect tag values)
2. The A.O. TIFF files were not directly readable by imagej, and matlab.
3. Ground truth was difficult to establish on some textured items and all items scanned in the presence of CT artifacts.
4. Difficult cases were present but not emphasized.
5. The scans were too oversampled leading to large data files.
6. Insufficient quality control was performed on the distributed databases.
7. DHS did not review datasets at time of receipt to detect QC issues
8. Scans of objects in isolation were purposely not made available to the Researchers due to template-matching concerns of Domain Experts.

5.9.2 Recommendations

1. Use an image format without headers and footers. This is known as a raw format.
2. Resample the images so that the pixel size matches the resolution of the images.
3. Use gzip or zip to compress files.
4. Perform additional quality control on the databases.
5. Use shorter filenames.
6. Retain the images of the phantom before each scan for QC and measurement validation.
7. Scan additional difficult cases.
8. Scan more homogeneous objects in different containers and levels of clutter and concealment.
9. Establish ground truth for all objects.
10. Revise or replace the Mevislab network used to develop the ground truth data.
11. Reduce manual intervention when developing the ground truth data.

5.10 Process Findings and Recomendations

5.10.1 Findings

1. Different object philosophies were used by program management, domain experts, database developers and researchers.
2. Acceptance (evaluation) criteria were not made clear at any point in the program and may have turned the segmentation project into a classification project.
3. The need for feature extraction was not sufficiently emphasized.
4. The duration of and funding for the project may not have been sufficient.
5. Communication with the researchers may have been insufficient, late and inconsistent.
6. Schedule for and definition of deliverables may not have been clear to the researchers.

5.10.2 Recommendations

1. Better specifications for acceptance criteria, databases and deliverables
2. Sample segmentation code and simple examples to understand inputs and outputs
3. Kickoff meeting for process and technical aspects
4. More group meetings: mentors and researchers
5. Develop evaluation criteria and distribute code
6. More time to evaluate results

6 Acknowledgements

The program management team would like to thank the following people and organizations for their involvement in the segmentation initiative.

- DHS S&T Explosives Directorate for funding ALERT and LLNL to implement this segmentation initiative.
- DHS S&T Office of University Program for providing the core funding for ALERT whcih includes the ADSA workshops which led to this segmentation initiative.
- Doug Bauer and Laura Parker, DHS S&T, and George Zarur, DHS & TSA (retired), for their vision to involve third parties in the development of technologies for security applications.
- Greg Struba and Earl Smith, DHS-Booz Allen support staff, for coordinating the participation of DHS and TSA.
- Rick Moore and Alyssa White (Massachusetts General Hospital) for dataset design, procurement, and management.
- The Domain Experts:
    - Carl Crawford, Csuptwo, LLC
    - Harry Martz, Lawrence Livermore National Laboratory
    - Homer Pien, Massachusetts General Hospital
- Mariah Nobrega for handling logistics for the project.
- Brian Loughlin, Mariah Nobrega and Rachel Parkin for providing logistical support for the symposium.
- Brian Loughlin and Rachel Parkin for taking the minutes during the symposium.
- The "Vendor" for working with ALERT to scan the luggage for the initiative's datasets on their medical scanner.

The segmentation initiative would not have been a success without the five research groups. The technical content of this report is due mostly to their contributions. We extend our heartfelt thanks to them for their participation.

7 Project Team

Principal Investigators and Program Management:

Michael Silevitch, Northeastern University
John Beaty, Northeastern University

Domain experts:

Carl Crawford, Csuptwo, LLC
Harry Martz, Lawrence Livermore National Laboratory
Homer Pien, Massachusetts General Hospital

Data Acquisition and Procurement

Rick Moore, Massachusetts General Hospital
Alyssa White, Massachusetts General Hospital

Unnamed Vendor

Database creation:

Rick Moore, Massachusetts General Hospital
Alyssa White, Massachusetts General Hospital

Tool developers:

Karina Bond, Lawrence Livermore National Laboratory
Carl Crawford, Csuptwo, LLC
Jeff Kallman, Lawrence Livermore National Laboratory
Seemeen Karimi, University of California, San Diego
Rick Moore, Massachusetts General Hospital
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Symposium logistics:

Rachel Parkin, Northeastern University
Mariah Nobrega, Northeastern University

SSI review:

Horst Wittmann, Northeastern University

8 Definitions

8.1 Acronyms

Acronym	Definition
2D	Two-dimensional
3D	Three-dimensional
ADSA	Algorithm Development for Security Applications (name of workshops at ALERT)
ADSA01	First ADSA workshop held in April 2009 on the check-point application
ADSA02	Second ADSA workshop held in October 2009 on the grand challenge for CT segmentation
ADSA03	Third ADSA workshop held in April 2010 on AIT
ADSA04	Fourth ADSA workshop held in October 2010 on advanced reconstruction algorithms for CT-based scanners.
ADSA05	Fifth ADSA workshop held in May 2011 on fusing orthogonal technologies
ADSA06	Sixth ADSA workshop to be held in November 2011 on the development of fused explosive detection equipment with specific application to advanced imaging technology
AIT	Advanced imaging technology. Technology for find objects of interest on passengers. WBI is a deprecated synonym.
ALERT	Awareness and Localization of Explosives-Related Threats, A Department of Homeland Security Center of Excellence at NEU
AT	Advanced technology
ATD	Automated threat detection
ATR	Automated threat resolution; a synonym of ATD.
BAA	Broad agency announcement
BLS	Bottle Liquids Scanners
CERT	Certification testing at the TSL
COE	Center of excellence, a DHS designation
COP	Concept of Operation
CPU	Central processing unit (a general purpose computer)
CRT	Certification readiness testing
CT	Computed tomography
DHS	Department of Homeland Security
DHS S&T	DHS Science & Technology division
DICOM	Digital Imaging and Communications in Medicine; http://medical.nema.org
DICOS	Digital Imaging and Communications in Security. NEMA standard for image format for security; NEMA IIC Industrial Imaging and Communications Technical Committee.
DoD	Department of Defense
EDS	Explosive detection scanner that passes TSL's CERT.
ETD	Explosive trace detection
EXD	Explosive detection directorate of DHS
FA	False alarm
FBP	Filtered back-projection
FOUO	For official use only

Acronym	**Definition**
FOV	Field of view
GC	Grand challenge
Gordon-CENSSIS	Center for Subsurface Sensing and Imaging Systems, a National Science Foundation Engineering Research Center at NEU
GPU	Graphical processing unit
HME	Homemade explosive
HVPS	High voltage power supply
IED	Improvised explosive device
IEEE	Institute of electrical and electronic engineers
IHE	Integrating the Healthcare Enterprise
IMS	Ion mobility spectrometry
IQ	Image quality
IRT	Iterative reconstruction technique
LAC	Linear Attenuation Coefficient
LLNL	Lawrence Livermore National Laboratory
Manhattan II	TSA procurement program for next-generation EDS. This term has been supplanted with the term Checked Baggage Inspection System (CBIS)
MBIR	Model based iterative reconstruction
MC	Monte Carlo [modeling]
MMW	Millimeter wave
MU	Marquette University
MV	Multiple view
NDA	Non-disclosure agreement
NDE	Non-destructive evaluation
NEMA	National Electrical Manufacturers Association
NEU	Northeastern University
NIST	National Institute of Standards and Technology
NQR	Nuclear Quadrupole Resonance
OOI	Object of interest
OSARP	On screen alarm resolution protocol/process
OSR	On screen resolution
OUO	Official use only
PD	Probability of detection
PFA	Probability of false alarm
PI	Principle Investigator
PPV	Positive predictive value
QR	Quadruple resonance
RFI	Request for information
ROC	Receiver operator characteristic
ROI	Return on investment or region of interest
RSNA	Radiology Society of North America
SAT	Site acceptance testing
SBIR	Small business innovation research
SCR	Siemens Corporate Research
SI	Segmentation Initiative
SIRT	Simultaneous iterative *reconstruction* technique

Acronym	Definition
SOC	Stream of commerce
SOP	Standard operating procedure
SPIE	International society for optics and photonics
SR	Statistical reconstruction
SSI	Sensitive security information
STIP	Security Technology Integrated Program
TBD	To be determined
THZ	Tera-Hertz imaging
TIP	Threat image projection
TQ	Threat quantity; minimum mass required for detection. Value(s) is classified.
TRX	TIP-ready x-ray line scanners
TSA	Transportation Security Administration
TSL	Transportation Security Lab, Atlantic City, NJ
TSO	Transportation security officer; scanner operator
TSS	Telesecurity Sciences
UEA	University of East Anglia
WBI	Whole body imaging; a deprecated term for AIT
XBS	X-ray back scatter
XDI	X-ray diffraction imaging
XRD	X-ray diffraction
Z	Atomic number
Zeff	Effective atomic number

8.2 Terms

Term	Definition
Classification	The processing a indicating which type of object in which category is present in a scan.
Detection	The process of creating a binary decision of the presence of absence of a specific type of object in a scan.
Feature extraction	The process of determining features of objects from their scans.
Features	Characteristics of objects such as mass, density and volume.
Identification	The process of cataloging items in scans in categories.
Scan	The set of images that results from scanning a piece of luggage on a CT scanner.
Segmentation	The process of associating voxels in scans to specific objects.
Ground Truth	A semi-automatic delineation of the segmented objects

9 Supplemental Material in the Appendices

The supplemental material listed in the following subsections is available in this interim final report.

All of the images shown in the supplemental material were obtained from scans on a commercial medical scanner. Explosives and explosive simulants were not scanned. Scans were not obtained on security scanners.

9.1 Symposium presentations

9.1.1 "Research Challenge Project Overview," Harry Martz, Carl Crawford and Homer Pien

Research Challenge Project Overview

Harry Martz, Lawrence Livermore National Laboratory
Carl Crawford, Csuptwo
Homer Pien, Massachusetts General Hospital

Executive Summary

- Objective: Bring new people (third parties) and ideas to segmentation of items in bags
- Do not expect third parties to solve the problem in a few months
- Five research groups (third parties) have applied/developed segmentation algorithms for volumetric CT scans of bags
  - Marquette University, Milwaukee
  - Siemens Corporate Research, Princeton
  - Stratovan Corp., Sacramento
  - Telesecurity Sciences Corp., Las Vegas
  - University of East Anglia, UK
- Developed quantitative scoring metrics
- Potential outcomes
  - Algorithms transition to fielded EDS
  - Researchers continue working on algorithms with TSA, ALERT and vendors
  - People trained to work in field
- Lessons learned by ALERT and researchers
  - Execution of initiative
  - Communication of specs and results
  - Novel algorithms
  - Process for engaging 3rd parties

2

Expectation Management

- Learning process for
  - DHS
  - ALERT
  - Researchers
- Lessons learned along the way
- Be patient!

3

Agenda

- History
- Objectives
- Process
- *Mea culpa*
- Futures
- Miscellaneous

- Details will be in final report
- Want to get the researchers on stage ASAP

HISTORY

5

DHS Goals

- Vendors doing an excellent job
- But, need
  - Increase probability of detection (PD)
  - Decreased probability of false alarm (PFA)
  - Detect more threats including wide-variation of home-made explosives (HMEs)
  - Reduced mass
  - Reduced labor costs
    - Eliminate human in the loop if possible
  - New algorithm ideas
  - New people
  - Development risk mitigation

6

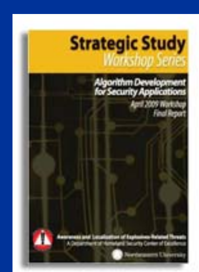
DHS Tactics

- Augment abilities of vendors with 3rd parties
  - Academia
  - National labs
  - Industry other than the vendors
- Create centers of excellence (COE) at universities
- Hold workshops to educate 3rd parties and discuss issues with involvement of 3rd parties
  - Algorithm Development for Security Applications (ADSA)

Vision created by George Zarur and Doug Bauer

7

ADSA01 - Recommendations



- Organize research challenges
  - CT first
    - Segmentation first
      - Easiest task to do first
      - Better features from segmentation will improve classifier
      - Classifier crown-jewels of vendors, especially features
    - Reconstruction second
      - Difficult to get projection data and parameters
  - Then other modalities
  - Then other aspects of generalized model
    - Sensor modeling and design
    - Human factors

8

Refinement

- "Grand challenge" cannot be used
  - Instead: research challenge, segmentation initiative, project or program
- ADSA02 discussed project details
- Classified meeting conducted with vendors
  - Mapped problem to public domain problem
  - Difficult configurations ≠ cannot detect

9

OBJECTIVES

10

Objectives

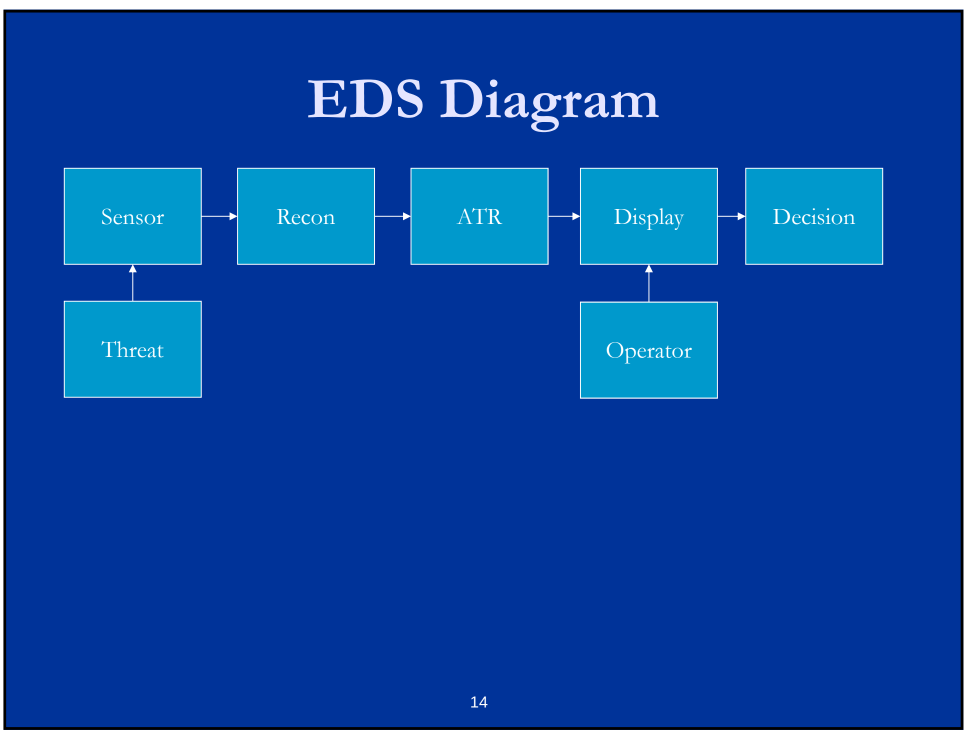
- Develop or apply *better* segmentation methods
  - Better precision on features such as mass, density
  - "Better" is difficult to define and assess
- Problem is that state-of-the art is proprietary to vendors
- Success measures
  - Engagement of third parties
  - Researchers in same room as vendors and DHS/TSA
  - Transition from third parties to vendors
  - Researchers receive funding from vendors and DHS
  - ALERT learns to work with 3rd parties and vice versa

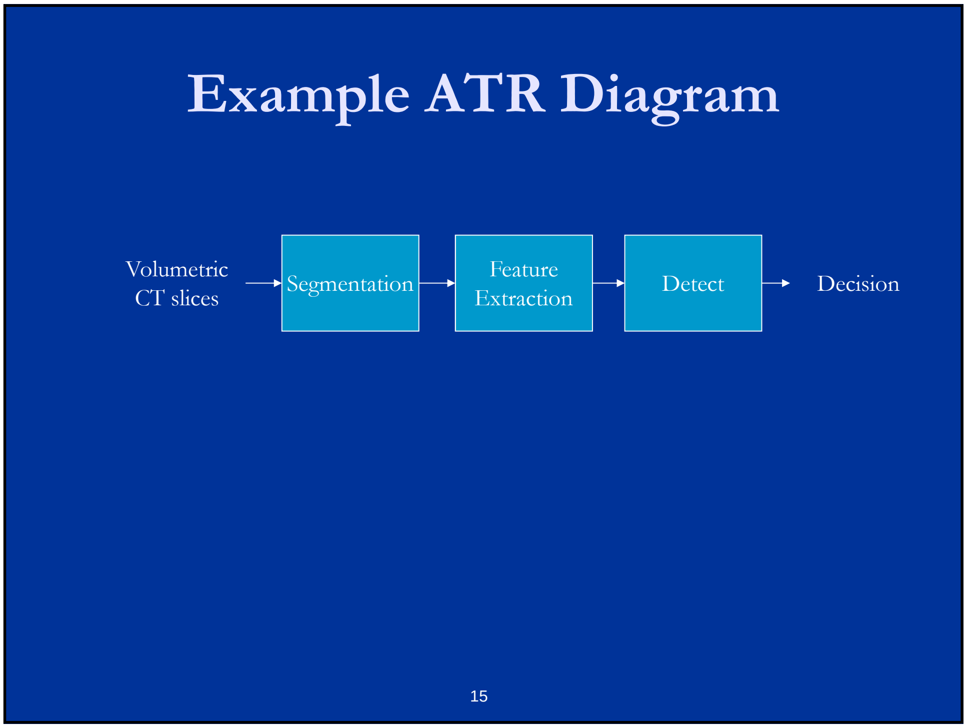
11

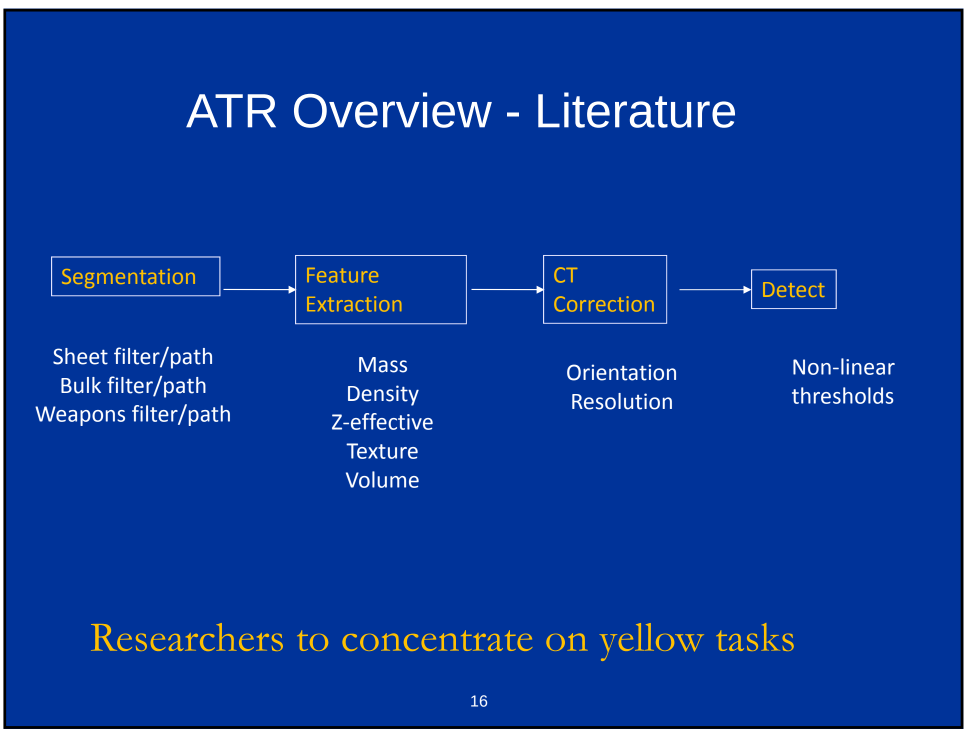
Object Philosophy

- From the RFP: "Candidates will use the project description, Qualification Dataset Group and their segmentation algorithms to segment objects (>500 [modified] Hounsfield units (MHU) and ≥50 mL, minimum) in the Qualification Dataset Group."
- Definitions purposely left open (denoted "object philosophy")
  - Physical objects v. components
  - Homogeneity of objects
- Want segment-all instead of segment threat-like objects
  - Threats will change over time
- Object classification and identification are out of scope

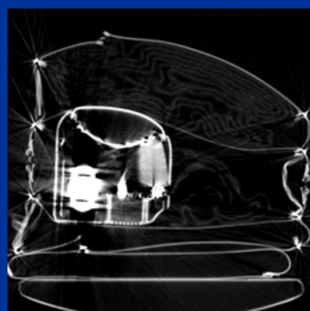

Object Philosophies
0:1001
0:1004
AA
Batteries
Piles
One physical object or N components?
13

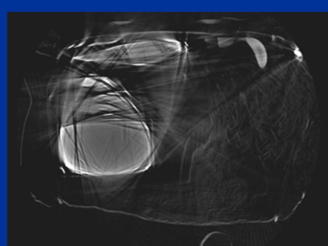

EDS Diagram
Sensor
Recon
ATR
Display
Decision
Threat
Operator
14


Example ATR Diagram
Volumetric CT slices
Segmentation
Feature Extraction
Detect
Decision
15


ATR Overview - Literature
Segmentation
Feature Extraction
CT Correction
Detect
Sheet filter/path
Bulk filter/path
Weapons filter/path
Mass
Density
Z-effective
Texture
Volume
Orientation
Resolution
Non-linear thresholds
Researchers to concentrate on yellow tasks
16

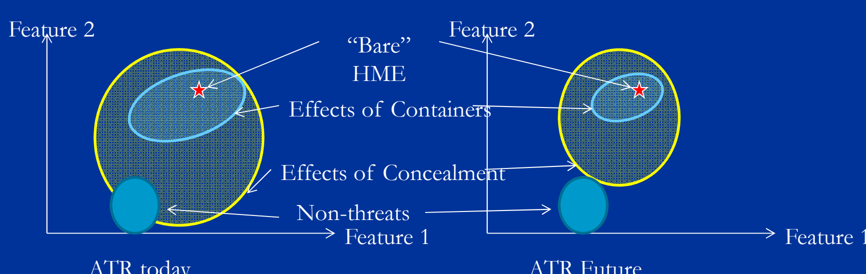
Cluttered Cross Sections





- Artifacts types
  - Shading
  - Streaks
  - Noise
  - Blurring
  - Rings
- Artifacts lead to
  - Merging of objects
  - Splitting of objects
  - Imprecise density, volume, mass, shape

Reduce Cluster Size



18

PROCESS

19

Steps

- DHS funding supplied to ALERT and LLNL
- Project plan written
- Proposals solicited
- Researchers chosen
- CT scans supplied
- Researchers develop algorithms
  - Mentorship provided by "Domain Experts"
- This symposium
- Final reports
  - Researchers
  - ALERT

20

Databases

- Packed suitcases with normal objects
- No threats, simulants or threat-like objects
- Scan on medical CT scanner
- Outline objects using semi-automated method
  - Denoted ground truth data
- Database packaged with packing videos and packing lists

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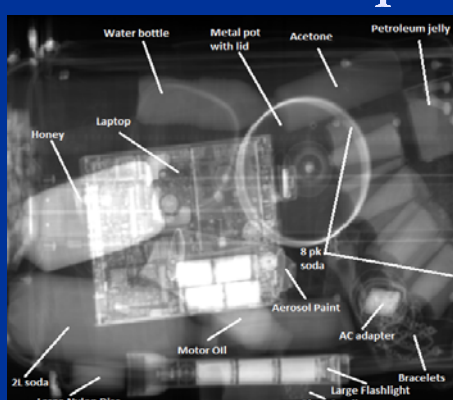
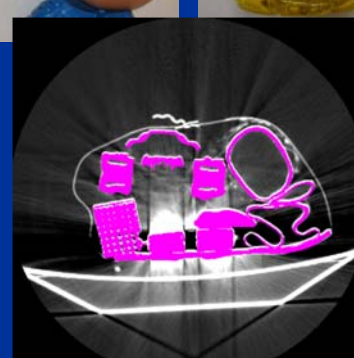
Sample Images





22

Team

- Program management (ALERT)
  - Michael Silevitch
  - John Beaty
- Database (Massachusetts General Hospital)
  - Rick Moore
  - Alyssa White
- Tool developers
  - Seemeen Karimi, University of California, San Diego
  - Jeff Kallman, Karina Bond, LLNL
- Domain experts (mentors)
  - Carl Crawford, Csuptwo
  - Harry Martz, LLNL
  - Homer Pien, Massachusetts General Hospital

23

MEA CULPA

24

Mea culpa (1)

- Object definition (or lack thereof)
  - Different object philosophies used by program management, domain experts, database developers and researchers
- Acceptance (evaluation) criteria
  - Not clearly defined
- May have turned into detection problem (not intended)
- Database
  - DICOM and TIFF files: Non-standard headers led to loading errors
  - Not enough scans of homogeneous objects in different configurations
  - Difficult cases not emphasized
  - Semi-automated method for generating ground truth had limitations, especially low-density and textured objects, and with CT artifacts: ground truth not ground truth
  - Quality control insufficient

25

Mea culpa (2)

- Not clear that segmentation included feature extraction (mass, density)
- Duration (~10 months) and funding ($70k) may not be sufficient
- Should have had more and earlier face time between researchers and mentors
  - More group communication

26

MISCELLANEOUS

27

EDS (CT) Vendors

- L-3 Communications
- Analogic
- Reveal/SAIC
- Morpho Detection (GE, Invision)
- Surescan
- Rapiscan

28

Researcher Presentations

- Speak for ~30'
- Discussion for ~30'
- Want real-time discussion
- Moderator to keep on time/track

29

Quiz

- What is the one sport in which neither the spectators nor the participants know the score or the leader until the contest ends?
- Today is not a contest and whatever it is will not end today!

30

9.1.2 "Report From The Evaluation Committee & Additional Discussion," Harry Martz, Carl Crawford and Homer Pien

Report From The Evaluation Committee & Additional Discussion

Carl Crawford, Csuptwo
Harry Martz, Lawrence Livermore National Laboratory
Homer Pien, Massachusetts General Hospital

Executive Summary

- Project has achieved its goals
  - Five research teams
    - Developed and applied novel segmentation algorithms
    - Learned about CT-based EDS and items in bags
  - ALERT
    - Learned how to involve third parties
    - Transform classified problem into public domain
- Future potential
  - Researches working with vendors, DHS and TSA to enhance their algorithms and transition to fielded systems
  - More involvement of third parties
  - Application to AIT, AT2, and other modalities

2

How Good Did They Do?

- All researchers were able to segment objects in bags
- Can't answer that question quantitatively for the following reasons.
  - Segmentation is part of ATR, which is trained to pass TSA EDS certification at TSL in Atlantic City at specific PD and PFA
    - Segmentation can also be separated from ATR to determine prevalence and features of non-threats
  - Objective was only segmentation
    - Not feature extraction and training with scans of explosives and stream of commerce data
  - Incumbent vendors' segmentation is proprietary
    - May be possible that all work presented today has been implemented by the vendors

3

How Far Did They Go?

- ADSA02 contained review of patent literature related to ATR for EDS
- Based on patents, researchers created novel methods
- Would need to implement patents to perform comparison

4

80-20 Rule May Apply

- Probably got 80% of the way to segmentation. However, five times as much effort is required to get last 20%.
  - Per Merzbacher (Morpho Detection), multiplier could be much greater … maybe 99-1 rule.

5

Common Strengths

- Understood problems caused by CT artifacts such as finite resolution and streaks, leading to merging and splitting of objects
- Implemented methods to compensate for splitting and merging
- Separate paths for some objects (e.g., sheets)
- Developed methods to score/evaluate results
- Dealt with object philosophies
- Potential to solve real security problems
- Patents filed

6

Specific Strengths

- Telesecurity
  - Sequential segmentation and carving
  - Bilateral filtering
  - Recursive k-Means clustering for splitting
- East Anglia
  - Sieves
  - Classifier
- Stratovan
  - Tumbler – kernel based segmentation
  - Automatic seed generation
- Marquette
  - Synthetic sinogram processing
  - Multi-path
  - Seed generation
  - Adaptive threshold
- Siemens
  - Synthetic sinogram processing
  - Confidence measure
  - 3D display

7

Time for Disclaimer

- Researchers and ALERT have done excellent work.
- Domain experts applaud all their efforts
- Next slides discuss opportunities for improvements
  - Should not be considered to be criticism of their work
- We bear some responsibility for weaknesses
  - Corollary of Heisenberg's Uncertainty Principle is that we could not observe without affecting
  - Did convince ALERT to overcome lessons learned with liquid threat detection project conducted by LLNL

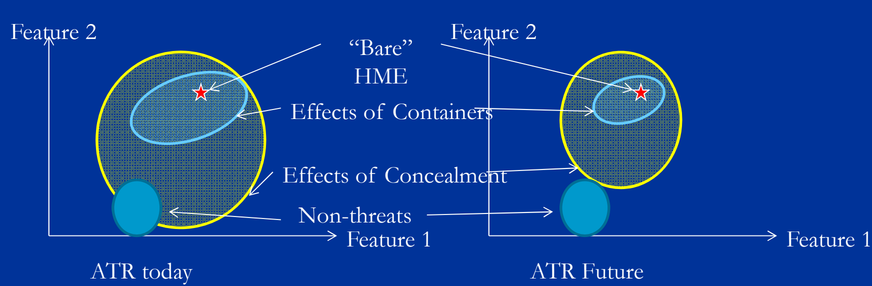
8

Improvement Areas

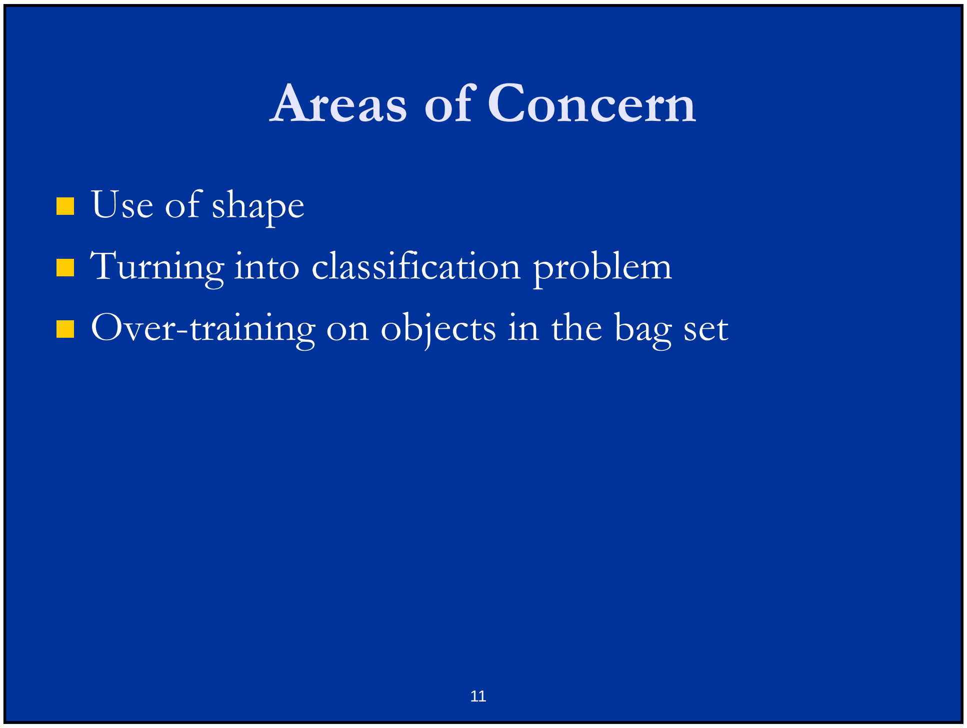
- Some difficult cases not sufficiently addressed
  - Easy to segment bulks in isolation
  - Difficult to segment bulks in presence of clutter and sheets artfully concealed
- Artifact reduction performed in projection space
- Feature extraction not sufficiently addressed
  - Precision and accuracy of mass, density
  - Means and higher order statistics

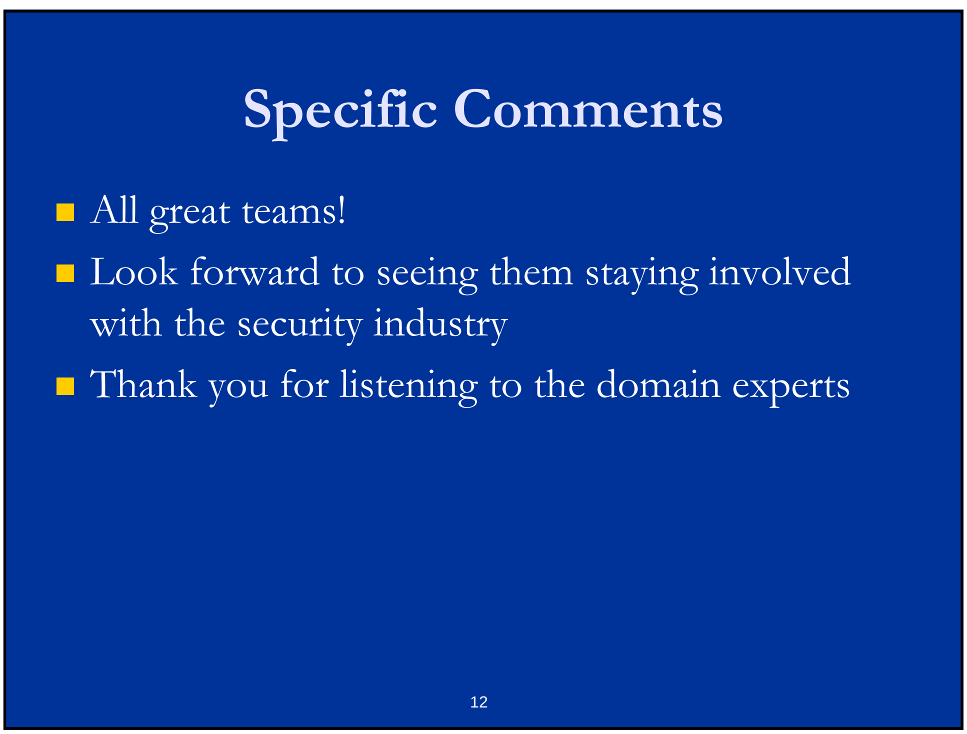
9

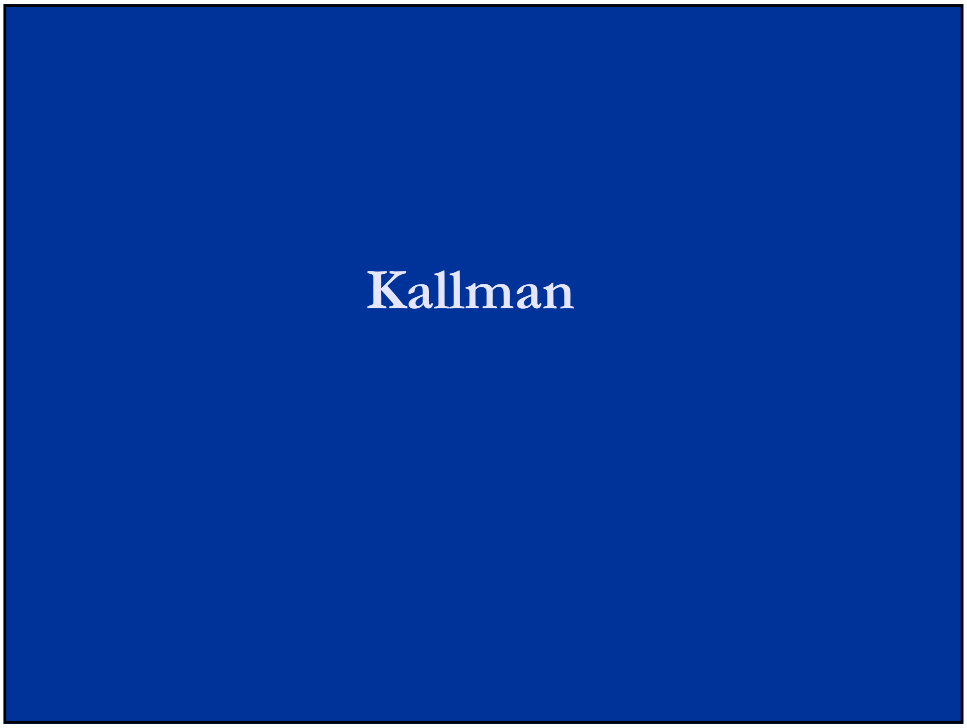
Reduce Cluster Size



10


Areas of Concern
Use of shape
Turning into classification problem
Over-training on objects in the bag set
11


Specific Comments
All great teams!
Look forward to seeing them staying involved with the security industry
Thank you for listening to the domain experts
12


Kallman

9.1.3 "Next Steps," Harry Martz, Carl Crawford and Homer Pien

Next Steps

Carl Crawford, Csuptwo
Harry Martz, Lawrence Livermore National Laboratory
Homer Pien, Massachusetts General Hospital

Recommendations

- Split into two projects
  - "Segment-all"
    - Prevalence studies can be performed
    - Classification based on object-types
  - Detect threats
    - Ultimate goal: pass TSA EDS Certification with better PD and PFA

2

Recommendations (2)

- Support research community
  - Funding
  - Forums & conferences
  - Databases into public domain
  - Evaluation methodology
- TSA purchases based on performance

3

Recommendation (3)

- Process changes for grand challenges
  - Better specifications for acceptance criteria, databases and deliverables
  - Sample segmentation code and simple examples to understand inputs and outputs
  - Kickoff meeting for process and technical aspects
  - More group meetings: mentors and researchers
  - Develop evaluation criteria and distribute code
  - More time to evaluate results

4

Researchers

- Derive quantitative evaluation metrics
- Revise presentations
- Complete final reports
- Publish
- Seek additional funding from
  - Vendors, DHS, TSA, ALERT
- Release code
- Revise algorithms
  - Artifact reduction
  - Feature extraction
  - Textured objects and sheets
- Develop ATR and try to certify

5

Program Management

- Complete final report
- Database and problem statements into public domain
- Facilitate community and networking

6

DHS

- Fund additional research by researchers, national labs and vendors
- Encourage vendors to engage third parties
- Choose more representative unclassified problems
  - AIT, AT2, cargo
- Provide access to image database at LLNL

7

Domain Experts

- Continue development of quantitative evaluation tools
- Better understanding of segmentation results
- Evaluate use of "evaluation database"

8

National Labs

- Execute segmentation algorithms on scans of threats and stream of commerce data
  - Use DHS image database at LLNL
- Compare with vendor ATRs

9

Vendors

- Compare proprietary segmentation to researcher segmentation
- Engage/hire researchers
- Provide more unclassified problems

10

Beyond Segmentation Challenge

- Additional grand challenges
  - ATR for CT and AIT
  - Reconstruction for CT, AIT, AT2
- Develop metrics for sub-systems
  - Reconstruction
  - Segmentation
- Advanced hardware development

11

The Structure of Scientific Revolutions Thomas Kuhn

Kuhn has made several notable claims concerning the progress of scientific knowledge: that scientific fields undergo periodic "paradigm shifts" rather than solely progressing in a linear and continuous way; that these paradigm shifts open up new approaches to understanding that scientists would never have considered valid before; and that the notion of scientific truth, at any given moment, cannot be established solely by objective criteria but is defined by a consensus of a scientific community. Competing paradigms are frequently incommensurable; that is, they are competing accounts of reality which cannot be coherently reconciled. Thus, our comprehension of science can never rely on full "objectivity"; we must account for subjective perspectives as well.

12

9.1.4 "Stratovan Decorum: Automatic Object Delineation from Checked Airport Baggage CT Scans," David Wiley, Jim Olson, Bernd Hamann, Deb Ghosh, and Christian Woodhouse, Stratovan Corporation

STRATOVAN decorum ™

Automatic Object Delineation from Checked Airport Baggage CT Scans

David F. Wiley, PhD *President and CTO*

ALERT Segmentation Symposium, December 08, 2011

2

Summary

- Robust and automatic delineation of objects irrespective of:
  - Topology
  - Shape
  - Orientation
  - Density
  - Touching objects
  - Thin objects
  - CT artifacts
- Novel segmentation technology: two patents filed
- Portable to the GPGPU*
- Integrated visualization and analysis of extracted objects
- Platform for automatic object detection

*GPGPU: General Purpose Graphics Processing Unit

3

STRATOVAN Background

- Founded in 2005.
- Startup from the Institute for Data Analysis and Visualization (IDAV) at University of California, Davis.
- 3D medical imaging, surgical planning, and treatment planning software.
- Products in orthopedic, craniofacial, neuroimaging, etc.
- Proprietary imaging platform called Encircle.

Proprietary and Confidential

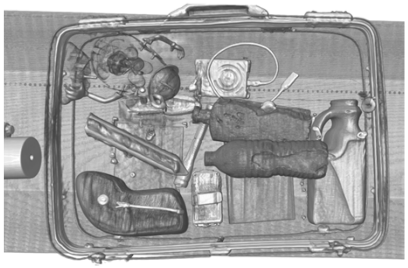
4

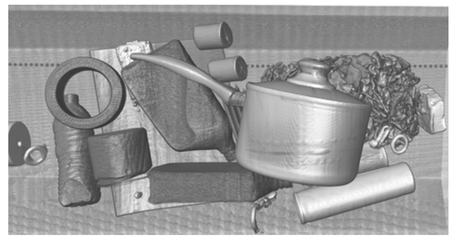
STRATOVAN Management and R&D

- **David F. Wiley, PhD**
  President and CTO
  - 20+ years in software
  - Medical imaging, user interfaces, software platforms, image processing
  - 25+ publications
- **Jim Olson, MBA** *CEO*
  - 30+ years in the Silicon Valley
  - Former CEO of SkyStream
- **Bernd Hamann, PhD** *Director*
  - Leading visualization scientist in the world
  - UC Davis Assoc. Vice Chancellor
  - 400 peer-reviewed papers over the last 20+ years
- **Deb Ghosh, PhD**
  Software Engineer
  - Geometric modeling, deformation, and feature detection,
- **Christian Woodhouse, BS**
  Application Developer
  - Imaging software and user interfaces

Proprietary and Confidential

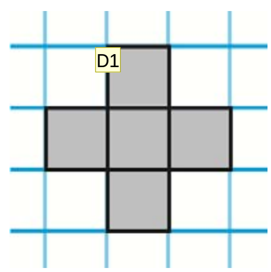
Problem Statement





- Automatic segmentation of objects from CT baggage scans
- No assumption of object types in bag
- Extract object features: mass, volume, and density
- Robust handling of:
  - CT artifacts
  - Streaking
  - Noise
  - Scattering
  - Ill-defined boundaries
  - New and unknown objects

Tumbler: Kernel-based Image Segmentation



- Define a 3D kernel
  - Multi-voxel, usually a sphere (4mm, 3mm, 2mm, or 1mm radius) D2
- Choose a start location
  - Automatically find “good” start locations
  - Add the neighboring voxels to a queue
- Define movement criteria (min, max, mean, std dev)
  - Determine thresholds that need to be satisfied to move kernel
- Iterative flood-fill process
  - Remove voxel position from queue and determine if the movement criteria is satisfied
  - If acceptable, move, add new neighbors to the queue and repeat

Slide 6

D1 determined from a trained function
1. voxel properties at start location
2. smaller than object, bigger than holes
3. "thickness" of the object

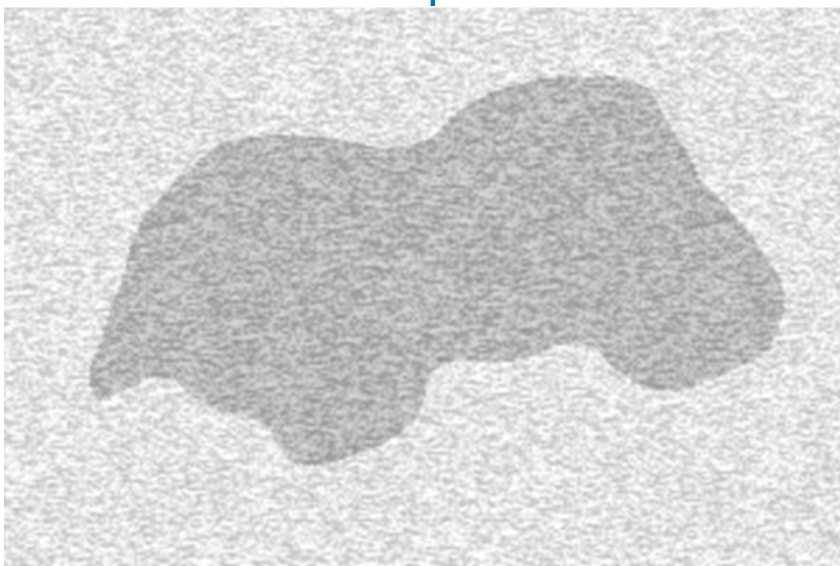
Deb, 11/29/2011

D2
1. Start in the center of homogeneous regions
2. avoid edges

Deb, 11/29/2011

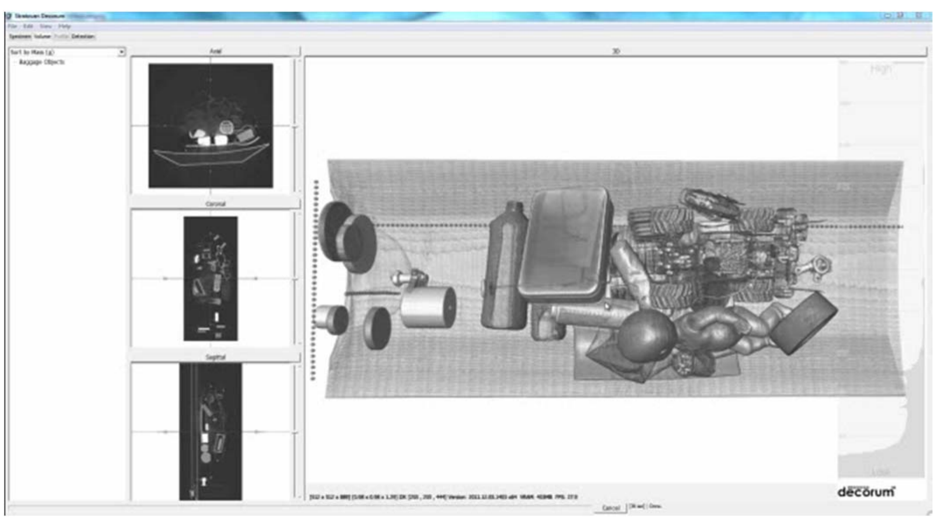
7

Tumbler: 2D Examples

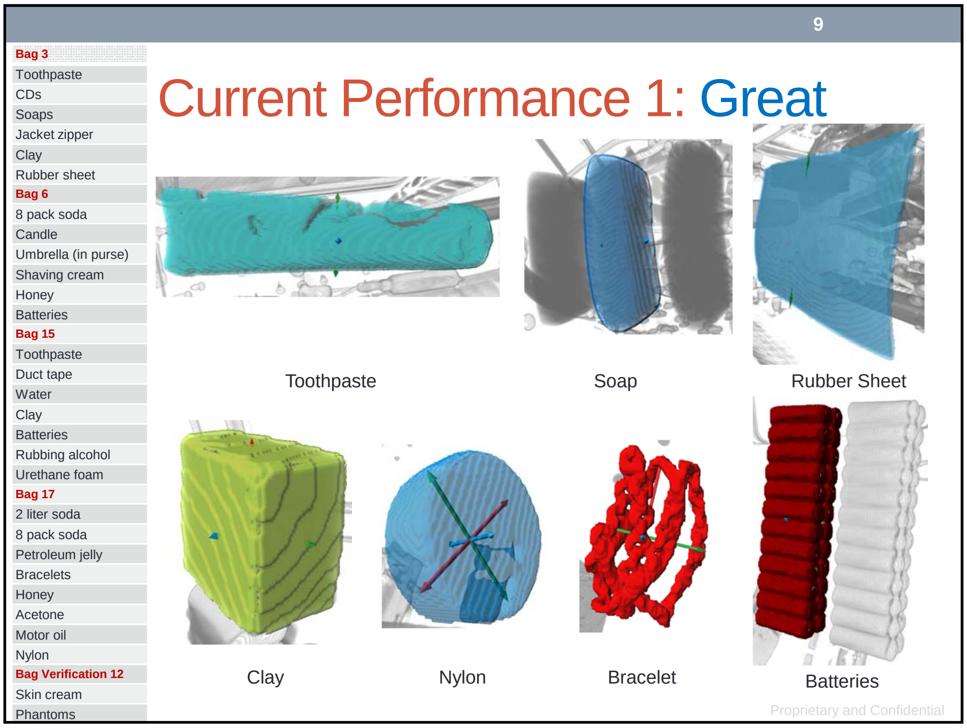


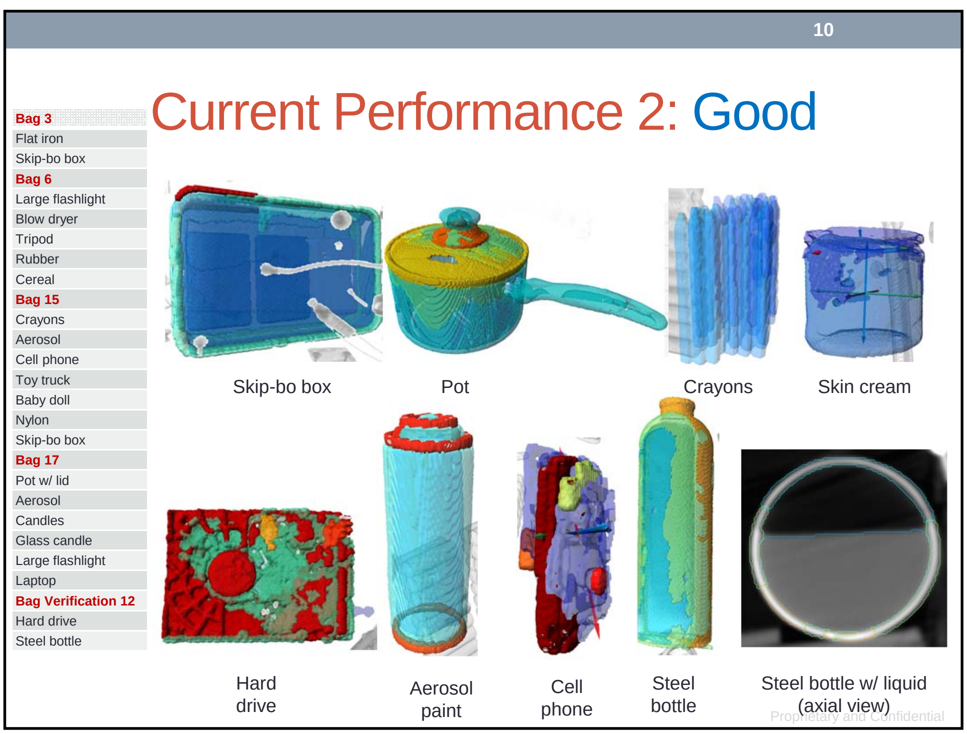
8

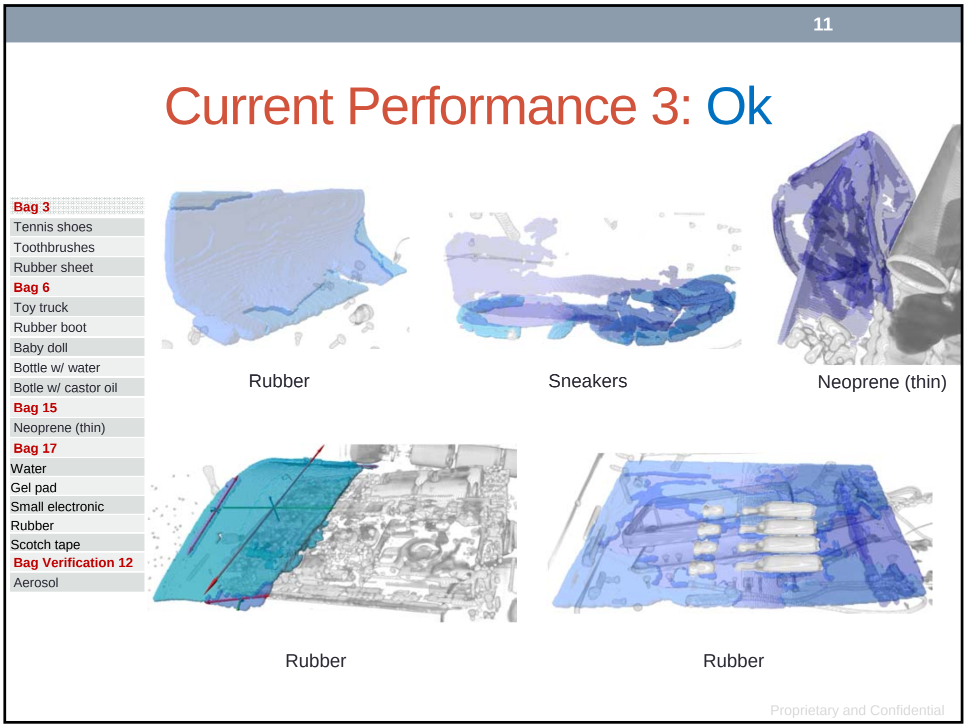
Bag 15 Segmentation

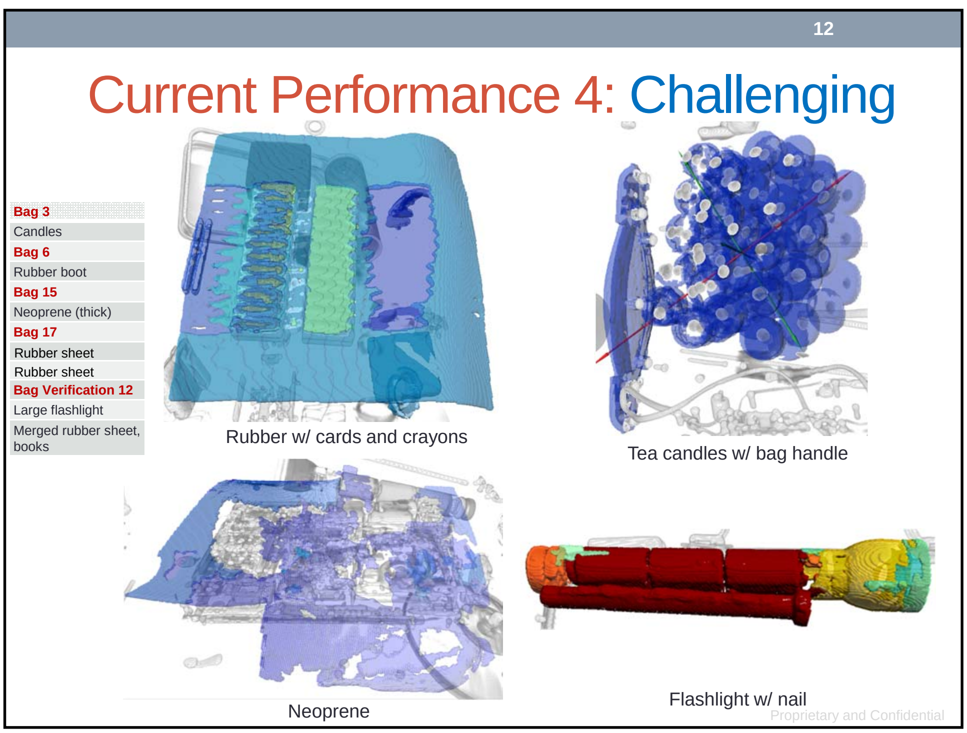


Demonstration video of Stratovan Decorum's automatic segmentation process.


9
Bag 3
Toothpaste
CDs
Soaps
Jacket zipper
Clay
Rubber sheet
Bag 6
8 pack soda
Candle
Umbrella (in purse)
Shaving cream
Honey
Batteries
Bag 15
Toothpaste
Duct tape
Water
Clay
Batteries
Rubbing alcohol
Urethane foam
Bag 17
2 liter soda
8 pack soda
Petroleum jelly
Bracelets
Honey
Acetone
Motor oil
Nylon
Bag Verification 12
Skin cream
Phantoms
Current Performance 1: Great
Toothpaste
Soap
Rubber Sheet
Clay
Nylon
Bracelet
Batteries
Proprietary and Confidential

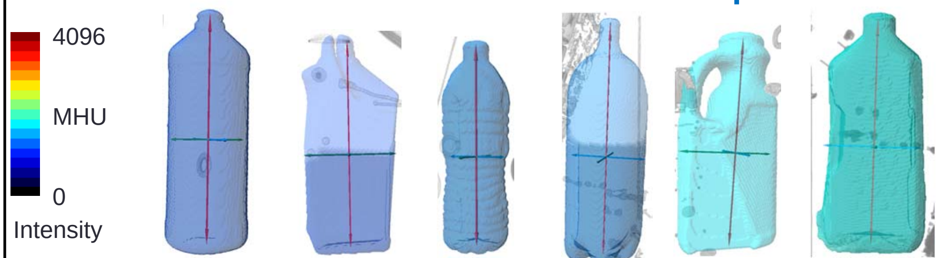

10
Bag 3
Flat iron
Skip-bo box
Bag 6
Large flashlight
Blow dryer
Tripod
Rubber
Cereal
Bag 15
Crayons
Aerosol
Cell phone
Toy truck
Baby doll
Nylon
Skip-bo box
Bag 17
Pot w/ lid
Aerosol
Candles
Glass candle
Large flashlight
Laptop
Bag Verification 12
Hard drive
Steel bottle
Current Performance 2: Good
Skip-bo box
Pot
Crayons
Skin cream
Hard drive
Aerosol paint
Cell phone
Steel bottle
Steel bottle w/ liquid (axial view)
Proprietary and Confidential


11
Current Performance 3: Ok
Bag 3
Tennis shoes
Toothbrushes
Rubber sheet
Bag 6
Toy truck
Rubber boot
Baby doll
Bottle w/ water
Botle w/ castor oil
Bag 15
Neoprene (thin)
Bag 17
Water
Gel pad
Small electronic
Rubber
Scotch tape
Bag Verification 12
Aerosol
Rubber
Sneakers
Neoprene (thin)
Rubber
Rubber
Proprietary and Confidential


12
Current Performance 4: Challenging
Bag 3
Candles
Bag 6
Rubber boot
Bag 15
Neoprene (thick)
Bag 17
Rubber sheet
Rubber sheet
Bag Verification 12
Large flashlight
Merged rubber sheet, books
Rubber w/ cards and crayons
Tea candles w/ bag handle
Neoprene
Flashlight w/ nail
Proprietary and Confidential

13

Current Performance 5: Liquids



	Rubbing Alcohol	Motor Oil 1qt	Water	2L Soda	Maple Syrup	Honey
Mean MHU	894	866	**1015**	1019	1286	1377
Std dev	22	25	**35**	30	66	69
Volume (cc)	1034	**907**	**489**	**2021**	978	1676
Mass (g)	924	785	**497**	2059	1258	2309

MHU = Modified Hounsfield Unit (water is 1000 MHU)
Volume is the sum of all segmented object voxels.
Variation in object metrics implies higher likelihood of detection discrimination.

14

Performance Summary

Easily segmented:
- High-intensity and high-gradient boundary objects
- Homogenous objects
- Heterogeneous objects can be “aggregated” based on overlapping voxels

Challenging:
- Low-intensity and low-gradient boundary objects
- Very thin/sheet-like objects (low contrast)
- Some heterogeneous objects do not have overlapping regions
- Clamped high-intensity objects that are touching

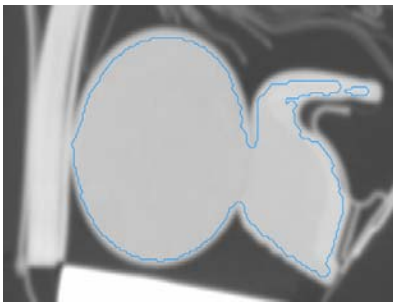
Homogenous object: i.e., **water**   Heterogeneous object: i.e., **cell phone**

15

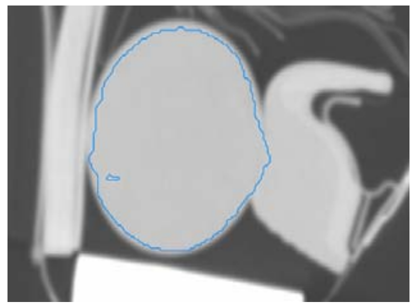
Splitting

Improve object splitting by optimizing:

- Kernel size
- Guiding threshold parameters



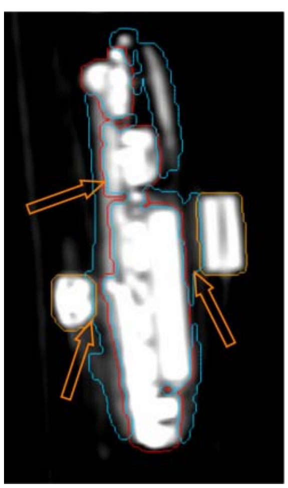
Kernel Radius: 2mm
Min: 750 MHU
Max: 1300 MHU



Kernel Radius: **4mm**
Min: 750 MHU
Max: **1055 MHU**

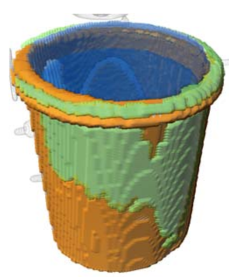
16

Merging

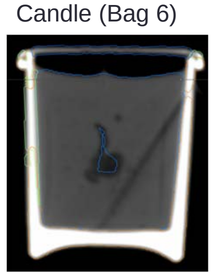


Overlapping voxels imply connectedness.

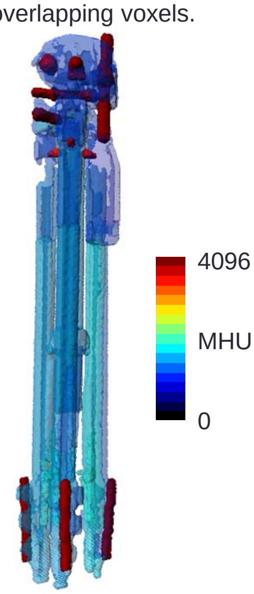
Automatic merging based on overlapping voxels.



Candle (Bag 6)



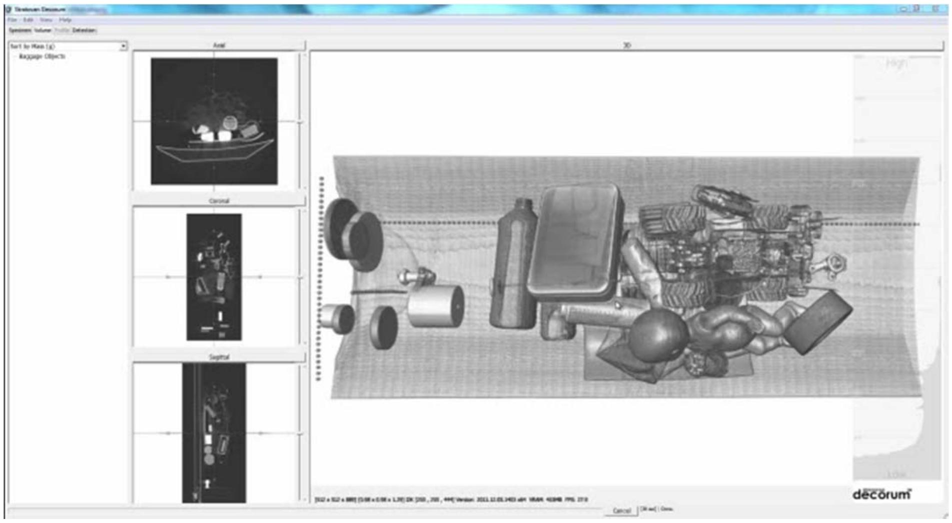
Candle (axial view)



Tripod (Bag 6)

17

Bag 15 Results



Demonstration video of Stratovan Decorum's object hierarchy and organization.

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Capabilities and Challenges

Capabilities:

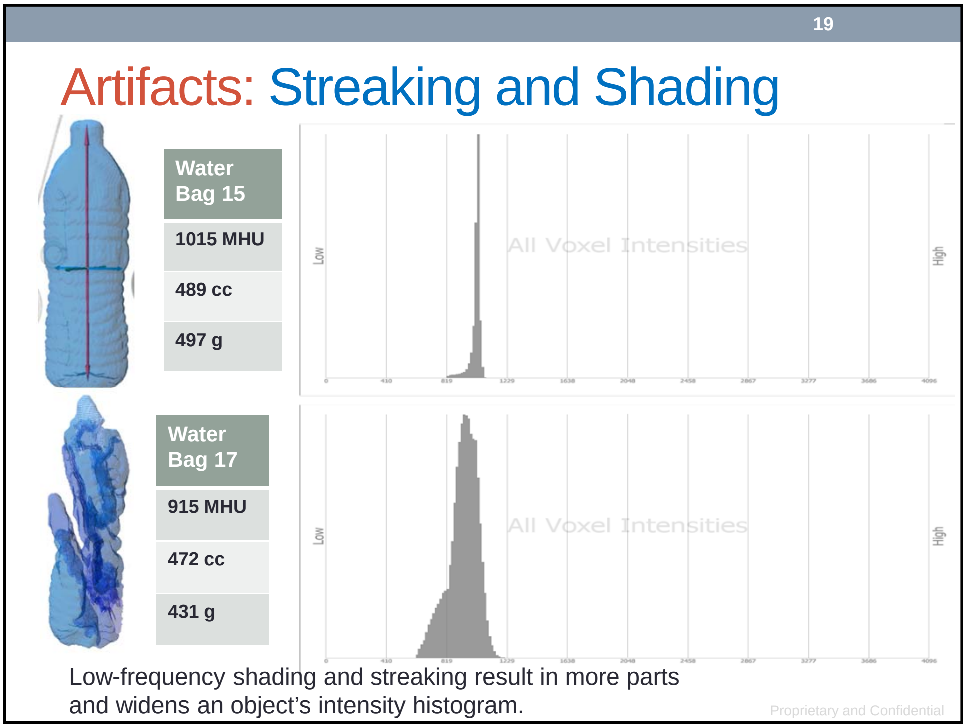
- No topological, size, shape, density, or mass constraints.
- No specific limitations on type of object.
- Smallest/thinnest object depends on CT resolution and contrast.

Challenges:

Low-intensity objects (<800 MHU):

- Have low contrast which poorly defines boundaries with other low-intensity objects.
- Are subject to noise, CT artifacts, etc.

CT spacing should be somewhat uniform: ideal is an aspect ratio better than 3:4.


19
Artifacts: Streaking and Shading
Water Bag 15
1015 MHU
489 cc
497 g
All Voxel Intensities
Low
High
Water Bag 17
915 MHU
472 cc
431 g
All Voxel Intensities
Low
High
Low-frequency shading and streaking result in more parts and widens an object's intensity histogram.
Proprietary and Confidential

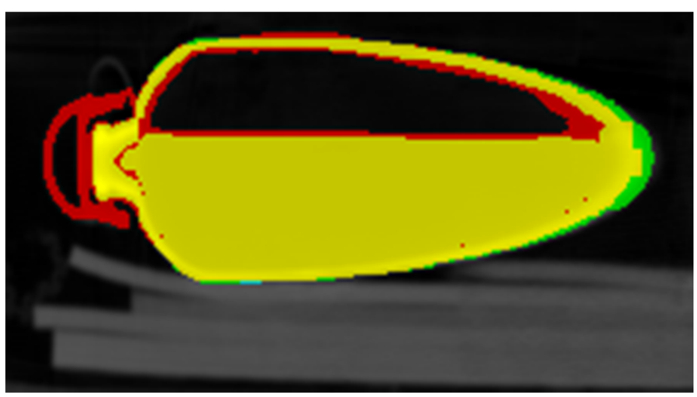

20
Artifacts : Streaking and Shading
Absolute Min: 42
Dynamic Min: 58
Dynamic Max: 97
Absolute Max: 10
Absolute Min: 730
Dynamic Min: 740
Dynamic Max: 974.8
Absolute Max: 1004.0

Ground Truth Comparison: Toothpaste

Color Key	
Yellow	Matched to ground truth
Red	In ground truth, but not in our segmentation
Green	In our segmentation, but not in ground truth
Blue	In our segmentation, but part of another object

Bag T 15

Ground Truth Comparison: Steel Bottle w/ Water

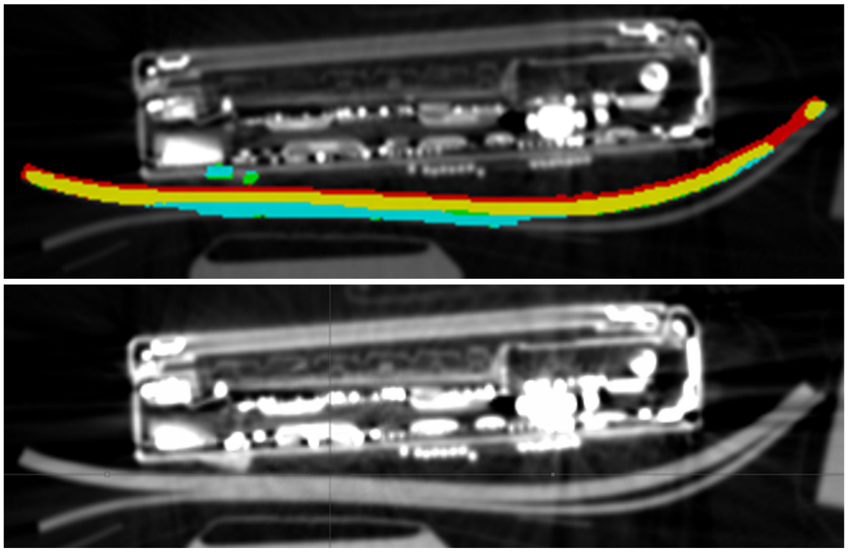


Color Key	
Yellow	Matched to ground truth
Red	In ground truth, but not in our segmentation
Green	In our segmentation, but not in ground truth
Blue	In our segmentation, but part of another object

Bag V 12

23

Ground Truth Comparison: Rubber Sheet



No boundary delineation exists between the stacked rubber sheets. Bag T 17

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Strengths and Weaknesses

Strengths:

- No topological constraints
- Easy to tune: seed, size, guiding criteria
- Tolerates noise and CT reconstruction artifacts
- Finds ill-defined boundaries
- Consistent results
- Easy to train
- Hardware agnostic
- Can be adapted to dual-energy scans (and fused data)
- Intuitive user interface
- Portable to GPGPU
- Platform for detection

Weaknesses:

- Low intensity objects (<800 MHU) due to low contrast
- Flat objects layered on top of each other (low CT resolution)
- Touching thin objects
- Relatively uniform voxel spacing
- CT reconstruction artifacts do change results

Risks and Mitigation

Inherent imaging issues (in order of importance):

- **Resolution:** uniform and small spacing (< 1mm) is ideal.
- **Low contrast:** filtering, improve bit representation, use floats.
- **CT artifacts:** improve reconstruction methods.
- **Calibration:** is water really 1000 MHU? Add phantoms to CT bed so they are captured in every scan.

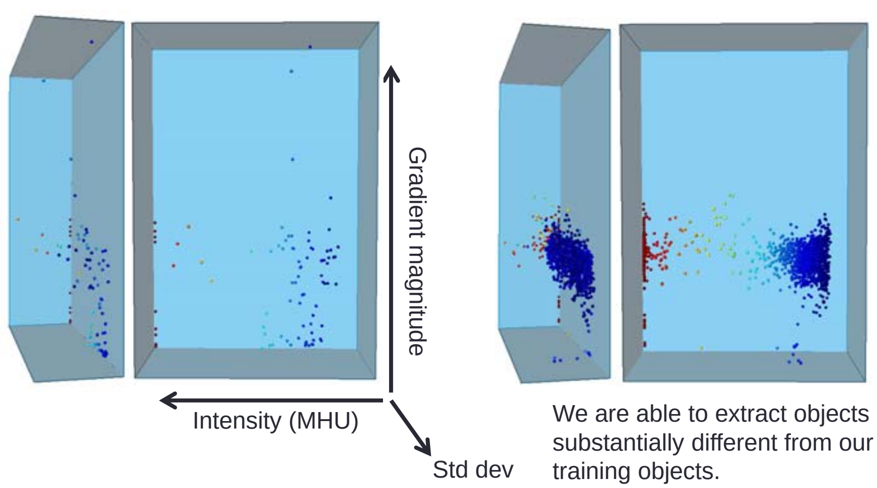
Software segmentation:

- **Topology:** spherical kernel can handle most shapes and topologies well.
- **Touching objects:** modify kernel shape and/or decrease pixel/slice spacing.
- **Never before seen objects:** cover our parameter space.

Risks and Mitigation: Training Parameter Space

87 Training points

Bag 6 – 1447 Objects/parts



We are able to extract objects substantially different from our training objects.

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Comments on Images, Reference Labels, Communications, and Acceptance Criteria

- **Images (minor issues):**
  - Pixel/slice spacing in DICOM incorrect
  - Slice order reversed
  - Incorrect DICOM tags in some bags
  - Bag numbering in packing reference offset (unpacking videos are crucial)
- **Reference labels (minor issues)**:
  - Some incorrect label numbers in ground truth
  - Voxel shifting in ground truth
- **Acceptance criteria:**
  - Difficult to ascertain "success," "failure," or "quality" quantitatively
  - Only focused on certain objects: water, book, cell phone, etc.
  - Does not adequately deal with the heterogeneous problem: laptop
- **Communication:** excellent, mentors were excellent, timely response, very supportive.

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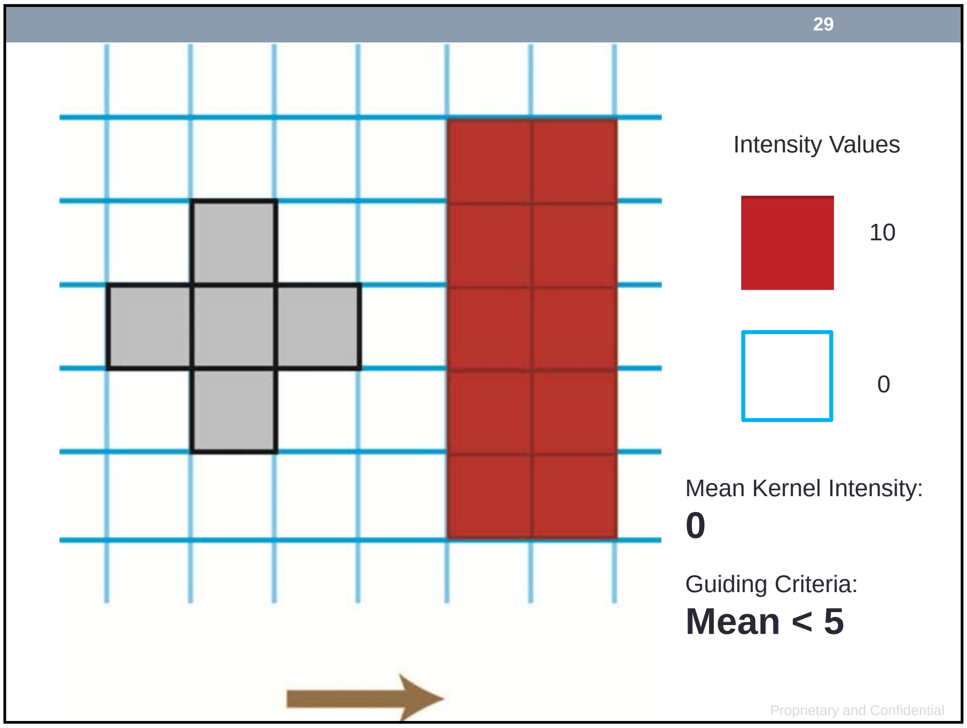
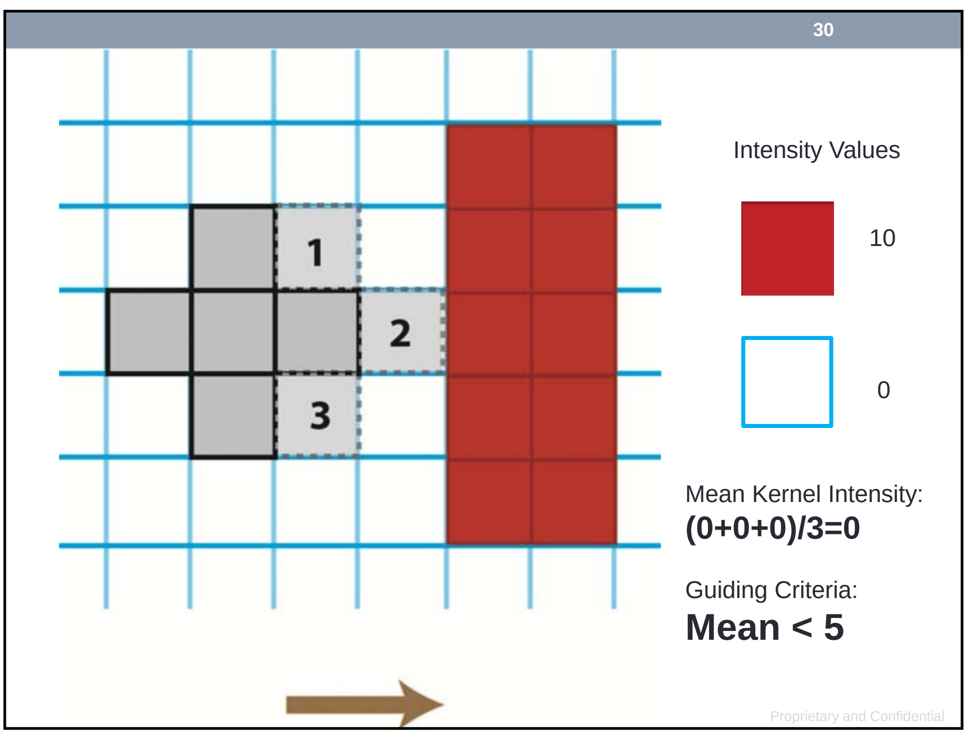
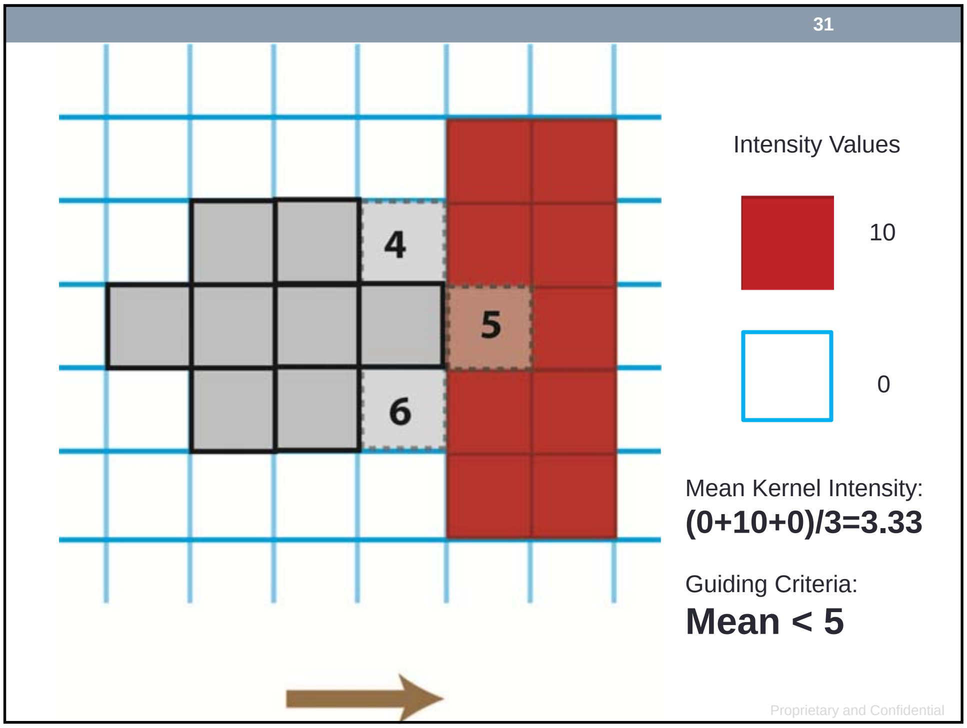
Future Work

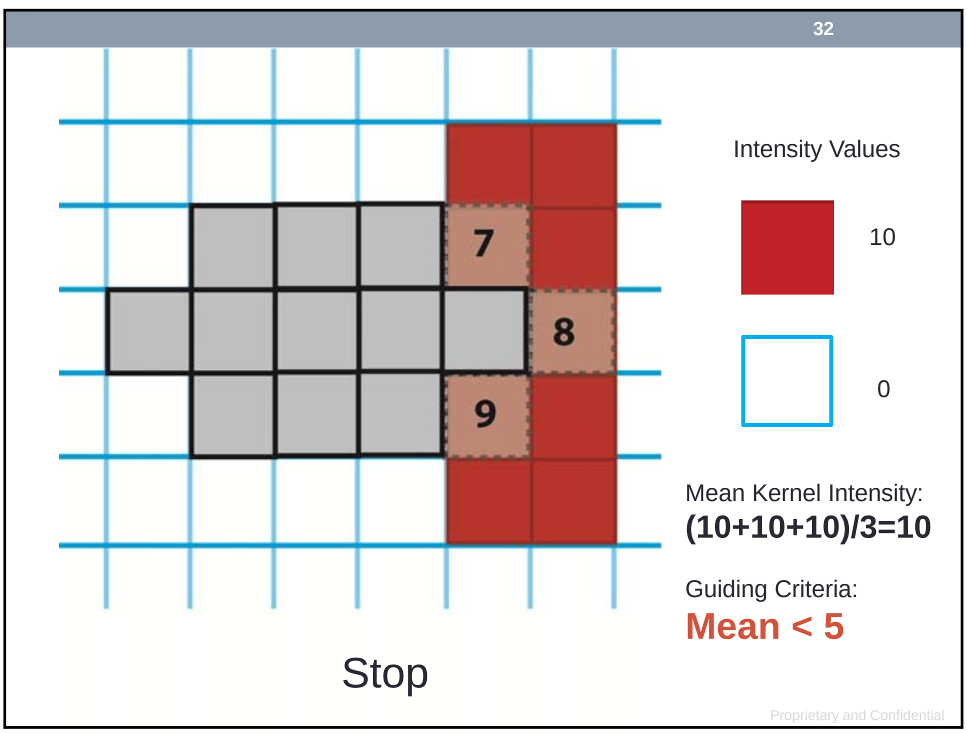
- Improve training to cover parameter space
- Improve aggregation to group object parts reliably
- Improve matching/detection system to perform "bottom-up" matching reliably
- Evaluate on scans from multiple equipment vendors
- Port to GPGPU
- Detection knowledge-base

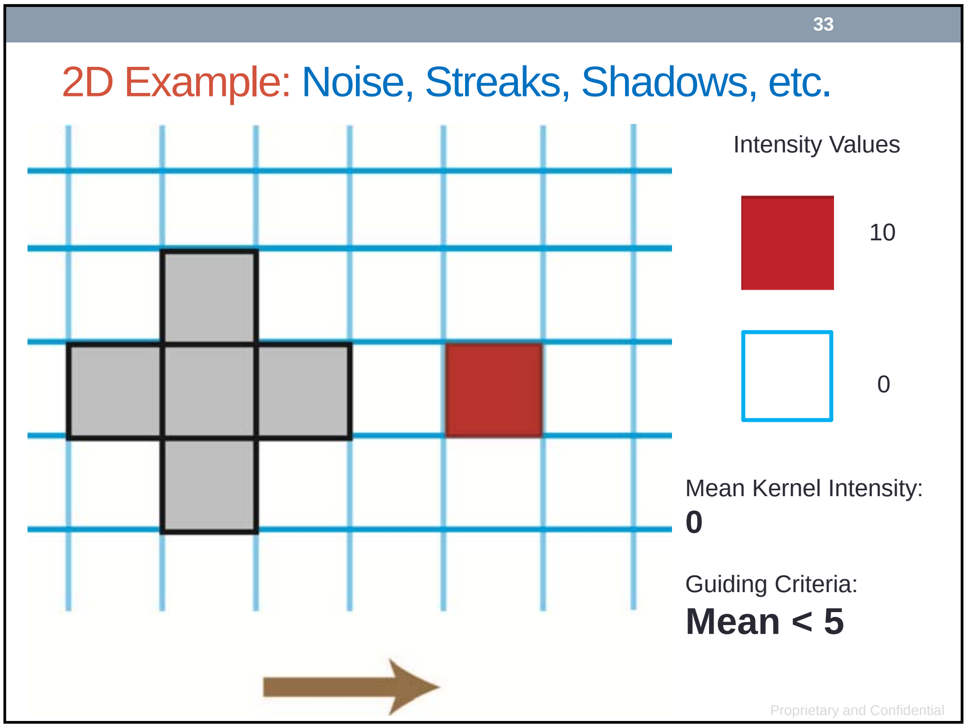
Contact: **www.stratovan.com**
David F. Wiley wiley@stratovan.com 916-813-7233
Jim Olson olson@stratovan.com 650-400-4046

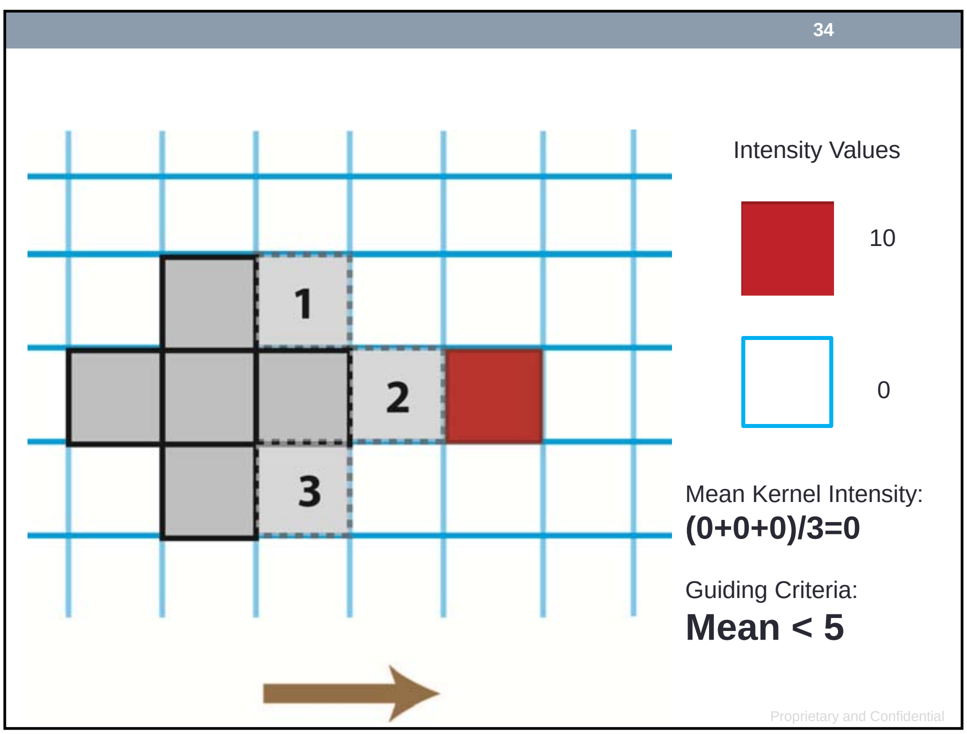

29
Intensity Values
10
0
Mean Kernel Intensity:
0
Guiding Criteria:
Mean < 5
Proprietary and Confidential

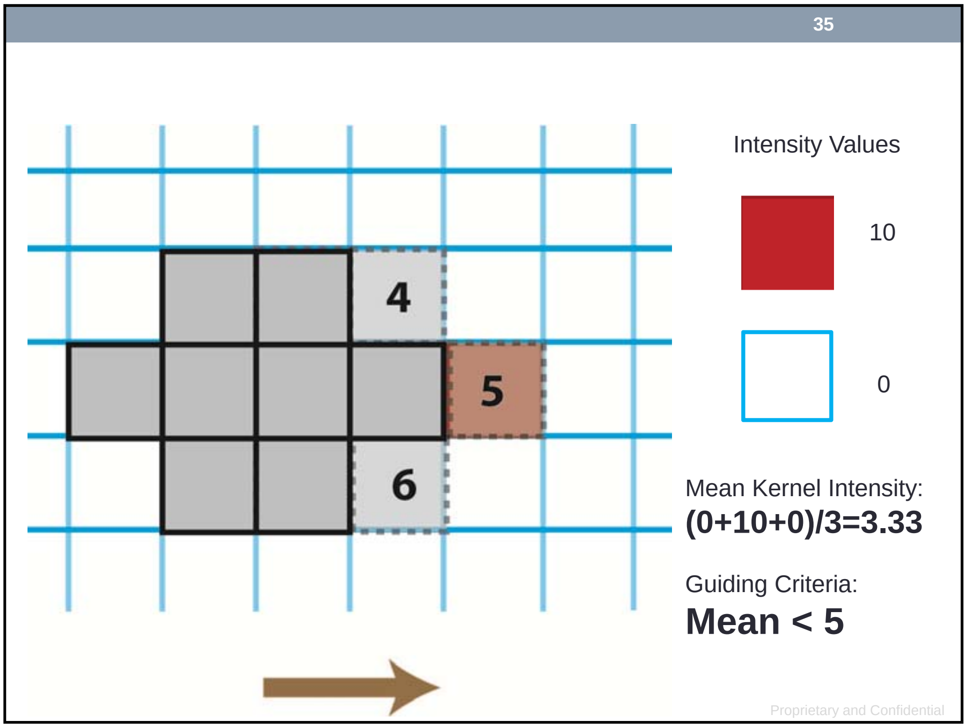

30
1
2
3
Intensity Values
10
0
Mean Kernel Intensity:
(0+0+0)/3=0
Guiding Criteria:
Mean < 5
Proprietary and Confidential

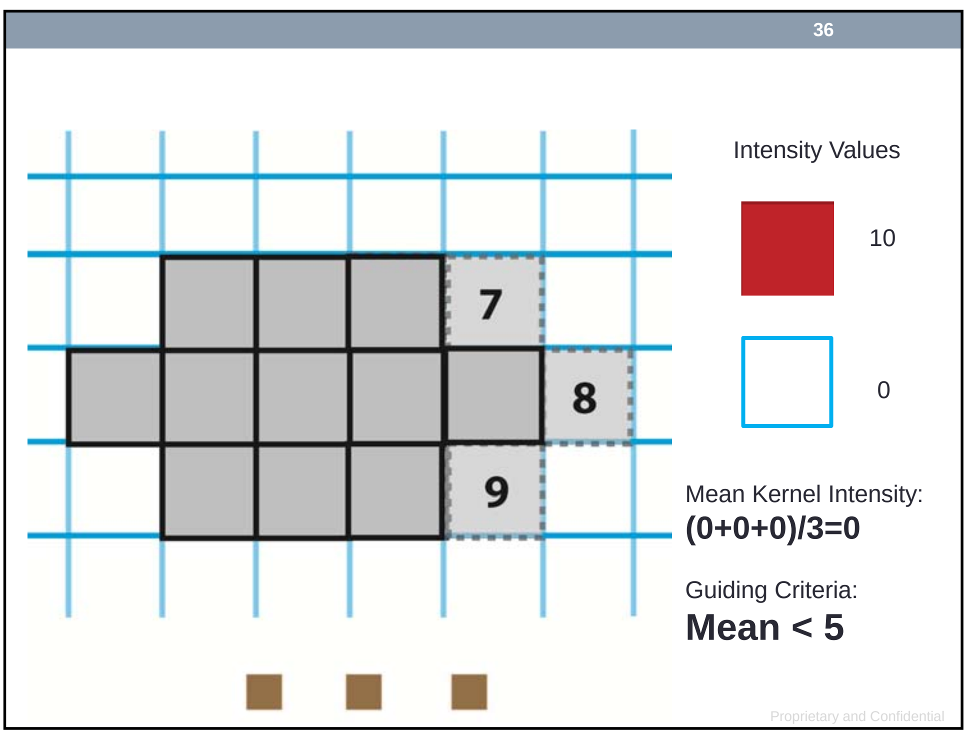

31
4
5
6
Intensity Values
10
0
Mean Kernel Intensity:
(0+10+0)/3=3.33
Guiding Criteria:
Mean < 5
Proprietary and Confidential


32
7
8
9
Intensity Values
10
0
Mean Kernel Intensity:
(10+10+10)/3=10
Guiding Criteria:
Mean < 5
Stop
Proprietary and Confidential


33
2D Example: Noise, Streaks, Shadows, etc.
Intensity Values
10
0
Mean Kernel Intensity:
0
Guiding Criteria:
Mean < 5
Proprietary and Confidential


34
1
2
3
Intensity Values
10
0
Mean Kernel Intensity:
(0+0+0)/3=0
Guiding Criteria:
Mean < 5
Proprietary and Confidential


35
4
5
6
Intensity Values
10
0
Mean Kernel Intensity:
(0+10+0)/3=3.33
Guiding Criteria:
Mean < 5
Proprietary and Confidential


36
7
8
9
Intensity Values
10
0
Mean Kernel Intensity:
(0+0+0)/3=0
Guiding Criteria:
Mean < 5
Proprietary and Confidential

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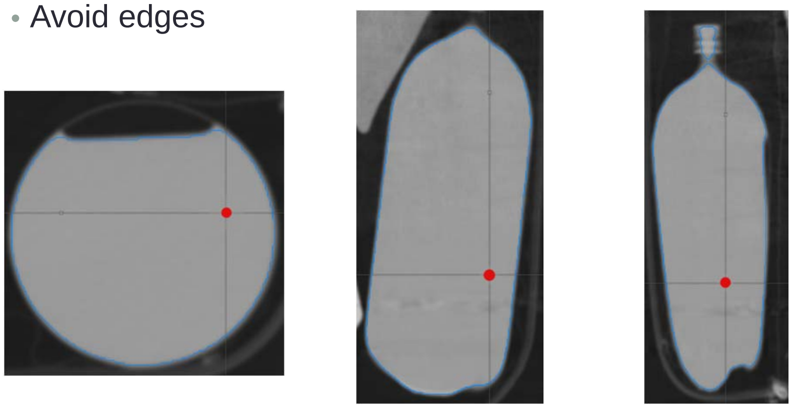
Tumbler Parameters: Choose a Start Location

- Start in the center of homogeneous regions
- Avoid edges



Starting location for 2L Soda bottle

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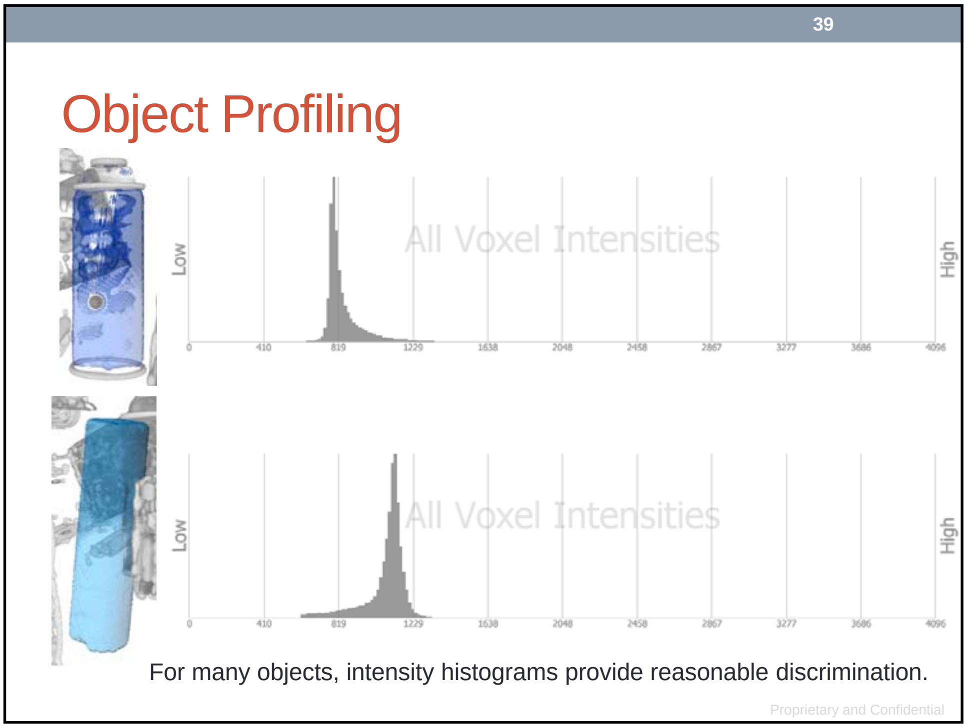
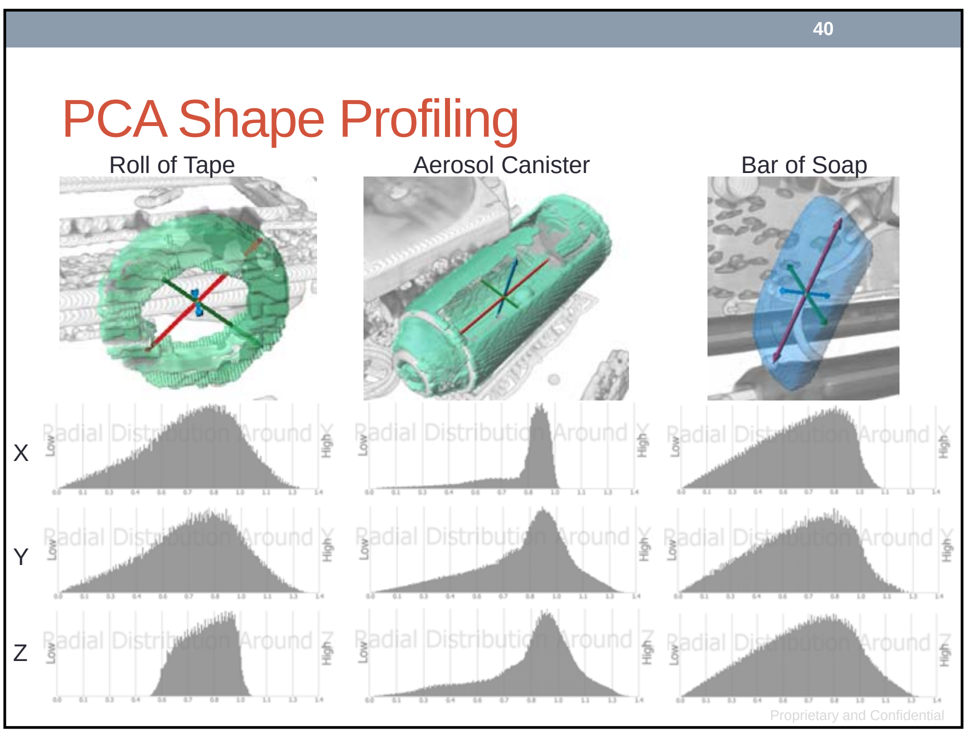
Seed Sorting

- Do large kernel sizes first, small last (4, 3, 2, 1mm)
- Do high intensity first, low intensity last (4096 to 0)
- Weigh “edges” less so we prefer to start in the middle of objects
- Take care to not penalize “thin” objects


39
Object Profiling
All Voxel Intensities
Low
High
0
410
819
1229
1638
2048
2458
2867
3277
3686
4096
All Voxel Intensities
Low
High
For many objects, intensity histograms provide reasonable discrimination.
Proprietary and Confidential


40
PCA Shape Profiling
Roll of Tape
Aerosol Canister
Bar of Soap
X
Radial Distribution Around X
Y
Radial Distribution Around Y
Z
Radial Distribution Around Z
Low
High
Proprietary and Confidential

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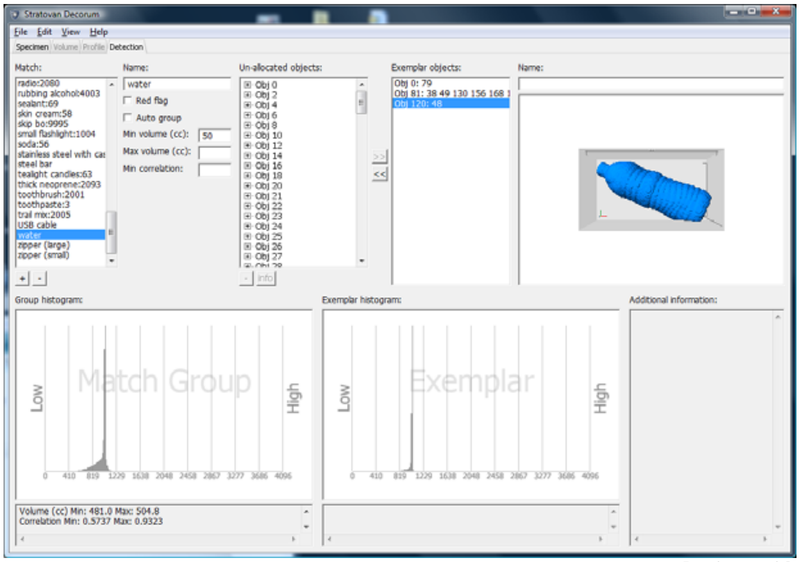
Detection Knowledge-base



9.1.5 "Extraction of Objects from CT Bag Images by Sequential Segmentation and Carving," Brandon J. Kwon, Samuel M. Song, Jason J. Lee, and Douglas P. Boyd, Telesecurity Sciences, Inc.

Extraction of Objects from CT Bag Images by Sequential Segmentation and Carving

Brandon J. Kwon, Samuel M. Song, Jason J. Lee, and Douglas P. Boyd

TeleSecurity Sciences, Inc.
7391 Prairie Falcon Road, 150-B
Las Vegas, NV 89128

December 8, 2011

Executive Summary

- Algorithm components
  - Pre-processing (edge preserving smoothing)
  - Parameterized Segmentation and Carving (SC)
    - Sequential SC using different sets of parameters for different objects
    - Carving out of segmented objects for next SC step
  - Post-processing
    - Splitting merged objects
    - Merging split objects
- Results
  - All homogeneous bulk objects in five focus cases are successfully segmented.
    - All merged objects are split and split objects are merged.
  - All sheets are detected (with some fragmentation)
  - Subject to definitions of object and homogeneity
- Future Work
  - Better segmentation of sheet objects

2

Our Definition of Object

- Object
  - Composed of physically contiguous ***homogeneous*** material
    - Homogeneity: difference in HU of contiguous voxels ≤ 50 (or thereabout)
- Segmented regions should be:
  - Homogeneous so that "features" can be estimated from MHU values
  - Large enough so that estimates can be determined with high confidence
- Ramifications
  - Cell phone
    - Three objects: plastic case, circuit board, battery
  - Two touching bottles
    - Of same liquid: 1 or 2 objects
    - Of different liquids, *e.g.*, water & alcohol: 2 objects
  - Candle (wax) in candle holder (glass)
    - 2 objects: candle and holder
  - Three soap bars in a paper container (not touching)
    - 3 objects

3

TeleSecurity Sciences, Inc.

- Start-up in Jan, 2006 by three founding members
  - Douglas P. Boyd, Ph.D., Hui Hu, Ph.D. and Samuel M. Song, Ph.D.
- Current Scientific Staff
  - Nine full-time and four part-time/consultants (most with advanced degrees)
- Development of Software Solutions for Security Imaging Systems
  - Automatic Target Recognition
    - EDS, AIT, AT/AT2, Cargo
  - CT Systems
    - Security and Medical
      - No-motion scanner design, reconstruction sub-system
- TSS has a working relationship with most security imaging system vendors
- Primary source of funding are contracts from DHS and industry
  - TSA contract related to CT segmentation project:

    Development of GUI for EDS (Prime Contractor: TASC)

4

TeleSecurity Sciences

Researchers

- Samuel M. Song, Ph.D.
  - Former professor (1995-2005), Ph.D. in Electrical Engineering
  - Experience in medical image processing, 3-D imaging and visualization, analysis of images, video applications, etc.
- Brandon J. Kwon, Ph.D.
  - Computer vision, analysis of video sequence for navigation applications, 3-D discrete reconstruction with few views, CT reconstruction, 3-D segmentation
- Jason J. Lee, M.S.
  - Image processing, dual-energy image analysis, ATR algorithms
- Douglas P. Boyd, Ph.D.
  - Founder/Founding Member of Imatron, InVision (now Morpho Detection), TeraRecon, AccuImage, TeleSecurity Sciences
  - Inventor of many novel CT applications, e.g., EBCT

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TeleSecurity Sciences

Problem Statement

- Perform automatic object segmentation of 3-D CT data of checked bags.
  - Requirements for objects to be segmented (from SOW)

    … has an average linear attenuation coefficient of ≥ 500 Modified Hounsfield Units (MHU), and aggregate pixel volume ≥ 50 mL.

- Our interpretation
  - Object be *homogeneous* as defined by region growing criteria,

    $|f(p) - f(q)| \leq c$ with $c \approx$ 50 MHU

  - Voxel size of $(\Delta x, \Delta y, \Delta z)$ = (0.98 mm, 0.98 mm, 1.29 mm)

    ➔ 50 cc = 40358 voxels imply virtually all objects except clothes.

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Overview of Our Approach

- Unsupervised Segmentation
  - Many advanced segmentation algorithms such as graph cut and many region growing approaches require seed points (user input).
- Our Tool Set and Contributions
  - *Bilateral Filter,* C. Tomasi and R. Manduchi (1998), Proc. ICCV.
    - Edge preserving smoothing filter (non-linear)
  - *Symmetric Region Growing*, S. Wan and W.E. Higgins (2003), *IEEE T. Image. Proc*
    - Finds all regions satisfying the symmetric region growing criteria $g(p,q) \equiv |f(p) - f(q)| \leq c$
    - Invariant to voxel processing order and fast implementation exists: $O(N)$
  - *Segmentation and Carving (SC)*
    - Repeated SC using different sets of parameters for different objects
    - Carving out of segmented objects for next SC step
  - *Split and Merge*
    - Split merged heterogeneous objects
      - RANSAC, recursive *k*-means
    - Merge homogeneous objects

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TSS Algorithm

Pre-processing → SC1 → SC2 → SC3 → SC4 → SC5 → Post-processing

- Preprocessing: Bilateral filter
- SC1: Homogeneous bulk objects
- SC2: Homogeneous medium thickness objects
- SC3: Homogeneous sheet objects
- SC4: Homogeneous metallic objects
- SC5: Remaining objects (heterogeneous)
- Post-processing: Split and Merge (histogram-based object splitting and merging)

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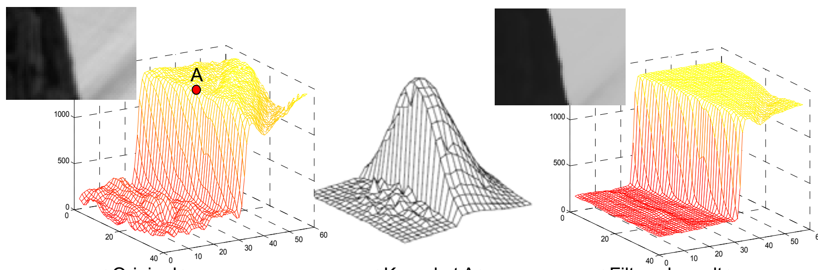
Pre-Processing—Bilateral Filter

- *Bilateral filtering for gray and color images* (1998), R. Tomasi and R. Manduchi, in *Proc. ICCV*.
  - *Earlier work: Non-linear Gaussian filters performing edge preserving diffusion* (1995), V. Aurich and J. Weule, in *Proc. DAGM Symposium.*
- Bilateral filtering: a smoothing filter that preserves edges

$$g(\mathbf{r}) = K\int_{\boldsymbol{\omega}} f(\mathbf{r})h_d(\boldsymbol{\omega}-\mathbf{r})h_r(f(\boldsymbol{\omega})-f(\mathbf{r}))d\boldsymbol{\omega},$$

where $h_d(\mathbf{r})$ and $h_r(\mathbf{r})$ are Gaussians, and *K is a scale factor so that DC gain is unity*



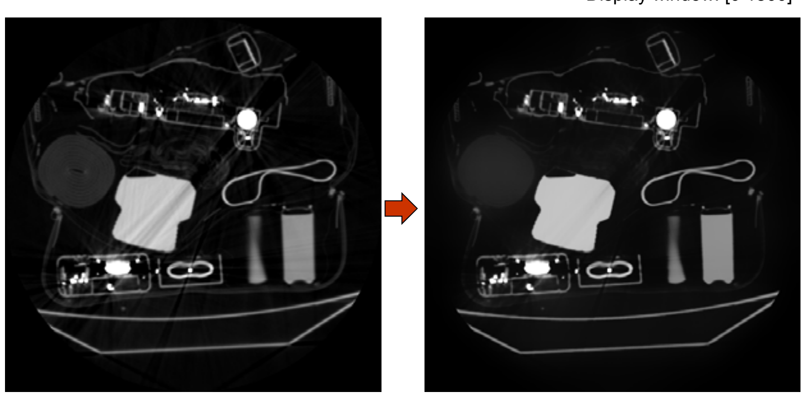
< Original > < Kernel at A > < Filtered result >

9

Bilateral Filter Output Example

- Application of bilateral filtering to CT images
  - We set $\sigma_d = 20, \sigma_r = 200.$

Display window: [0 1800]

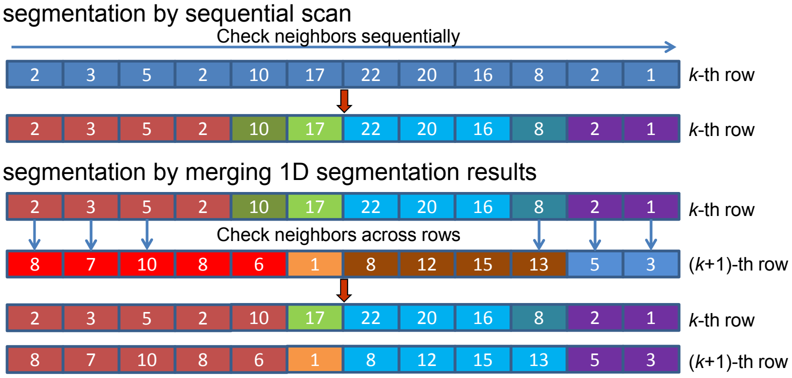


< Original > < After bilateral filtering >

10

Symmetric Region Growing

- SRG with $g(p,q) \equiv |f(p) - f(q)| \leq c, c = 4$
  - 1D segmentation by sequential scan
  - 2D segmentation by merging 1D segmentation results



    - If any two pixels satisfy $g(p,q)$, their labels are merged.
  - 3D segmentation by merging 2D segmentation results
    - Check neighbors across slices

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Segmentation and Carving—Overview

- In SRG, different c results in characteristically different objects by selectively processing voxels within a window of MHUs, $I_1 \leq f \leq I_2$.
  - Segmentation and Carving: SC(I_1, I_2, c)
    - Threshold: mask = 1, if $I_1 \leq f \leq I_2$
    - Perform object dependent processing of the binary mask
    - Perform SRG(c) : $g(p,q) \equiv |f(p) - f(q)| \leq c$
    - Carve out the segmented result for the next SC step
- Sequential application of SC
  - SC1: SC(600,2000,50) for homogeneous bulk objects
  - SC2: SC(600,2000,50) for homogeneous medium thickness objects
  - SC3: SC(400,1500,50) for homogeneous sheet objects
  - SC4: SC(3700, MAX, 30) for homogeneous metallic objects
  - SC5: SC(1200, MAX, 300) for all remaining objects (heterogeneous)

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Segmentation and Carving—Specifics

- Processing of the segmented binary mask
  - SC1 and SC2
    - Includes opening (erosion + dilation) with structuring element, SE = $N \times N \times N$ cube
      - Removes regions whose thickness is less than N
      - $N = 11$ for SC1 (bulk objects)
      - $N = 5$ for SC2 (medium thickness objects)
  - SC3, SC4, and SC5
    - Includes Weak Connection Removal (also clean up small remaining regions)
      - Convolve the 3-D mask with a $7 \times 7 \times 7$ kernel of 1's
      - Remove voxels whose count < threshold (80)

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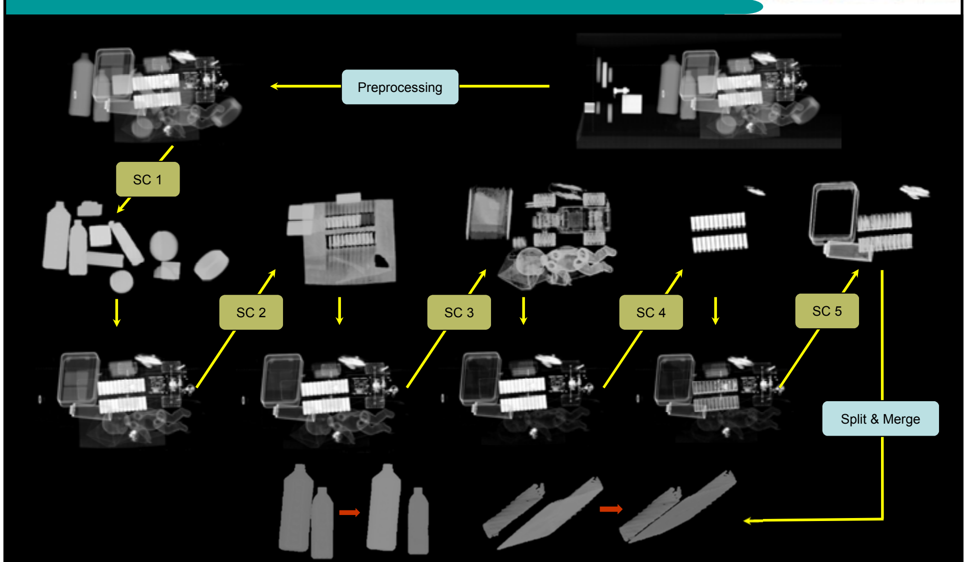
Sequential Application of SC



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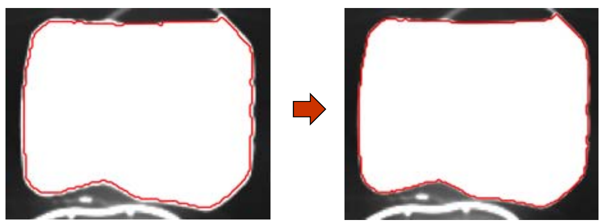
Volume Compensation –Active Contour using Level Set

- The boundaries as determined by SC are inaccurate. We adjust the boundaries by the level set technique.
  - *Active contours without edges*, T.F. Chan and L.A. Vese (2001), *IEEE T. Img. Proc.*. Level set curve minimizing Mumford-Shah energy functional

$$E(C, c_1, c_2) = \mu \cdot \text{Length}(C) + \lambda_1 \int_{in(C)} |u_0(x,y) - c_1|^2 \, dxdy$$

$$+\lambda_2 \int_{out(C)} |u_0(x,y) - c_2|^2 \, dxdy$$

- Used for volume compensation for objects from SC1



15

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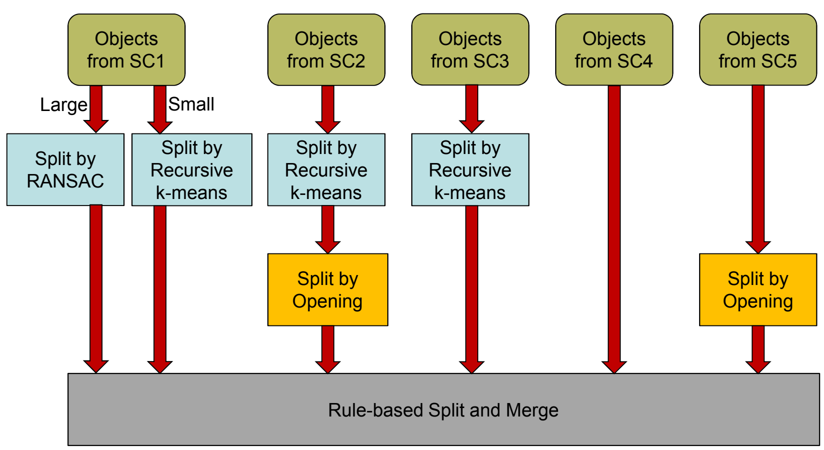
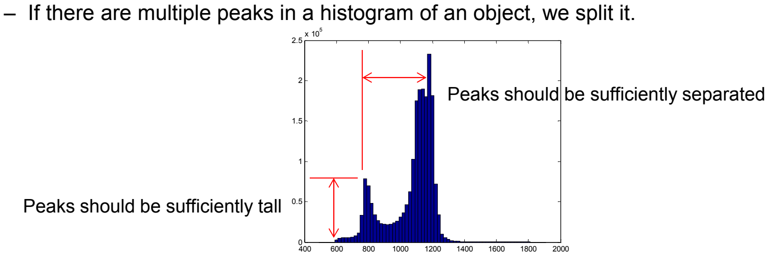
Object Splitting & Merging—Flow Chart



16

Object Splitting—Overview

- Histogram analysis for segmented objects
  - If there are multiple peaks in a histogram of an object, we split it.



- We apply this histogram analysis for objects segmented from SC1, SC2, and SC3.
  - SC4: All segmented objects are virtually homogeneous → No need for histogram analysis
  - SC5: Heterogeneous objects → No need for histogram analysis

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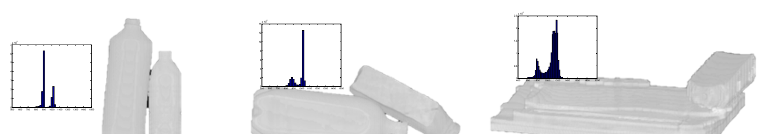
Object Splitting for Bulk (SC1) Objects—Step 1

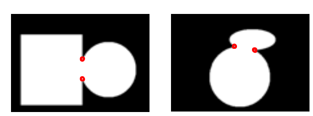
- Merged object cases from SC1 found by histogram analysis



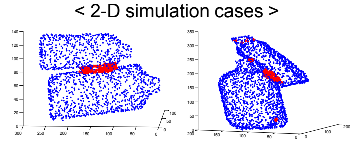
from T15 from T17 from V12

- These "large" merged objects are split as follows

- Step 1. Merged point detection
  - At each boundary voxel, calculate the number of object voxels within a $11 \times 11 \times 11$ window surrounding the voxel.
  - At the point where objects are merged, such numbers are usually much greater than those at other boundary points.



< 2-D simulation cases >

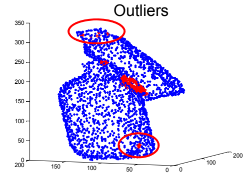


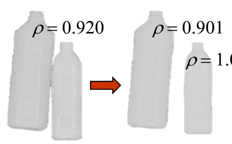
< 3-D real cases >

18

Object Splitting for Bulk (SC1) Objects—Step 2

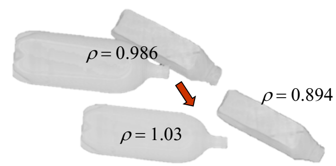
- Step 2. Splitting using a plane fitted by RANSAC
  - RANSAC (Random Sample Consensus)
    - An iterative method to estimate parameters of a model from a set of observed data robust against outliers
  - We fit a 3-D plane for the detected merged points by RANSAC
    - The plane can be found accurately in spite of outliers.
  - The objects are split by the fitted plane.





from T15 (70% Isopropyl Alcohol and Water)

from V12 (Organic Stack and Aerosol Metallic Paint)

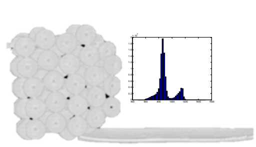


from T17 (Mountain Dew and Motor Oil)

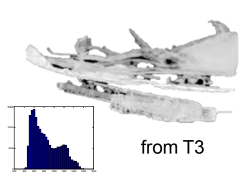
19

Object Splitting for Small SC1 Objects and SC2/SC3 Objects

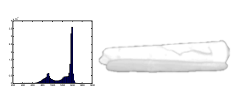
- Small SC1 Objects and SC2/SC3 Objects
  - Utilize recursive *k*-means clustering not relying on the shape property because shapes are usually irregular.
  - Recursive *k*-means with $k = 2$ until all objects pass the histogram analysis test.



from T3



from T3

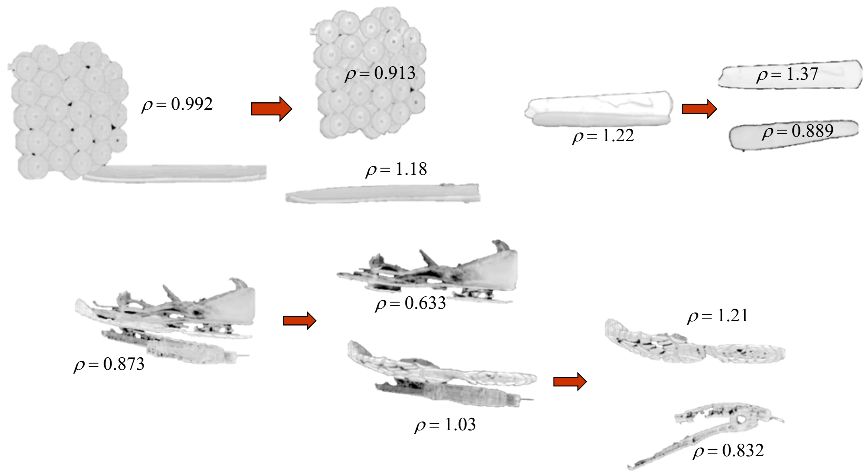


from T3

20

Recursive k-Means Clustering

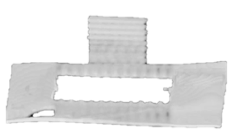
- Splitting results by recursive *k*-means clustering



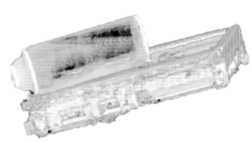
21

Object Splitting by Opening

- SC2 and SC5 Merged Object Splitting



from T15 (segmented from SC 2, after histogram analysis)



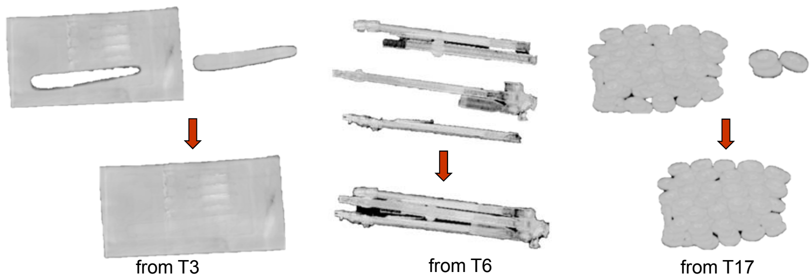
from T17 (segmented from SC 5)

- We finally split these objects by morphological opening
  - Objects removed by opening are thin objects.

22

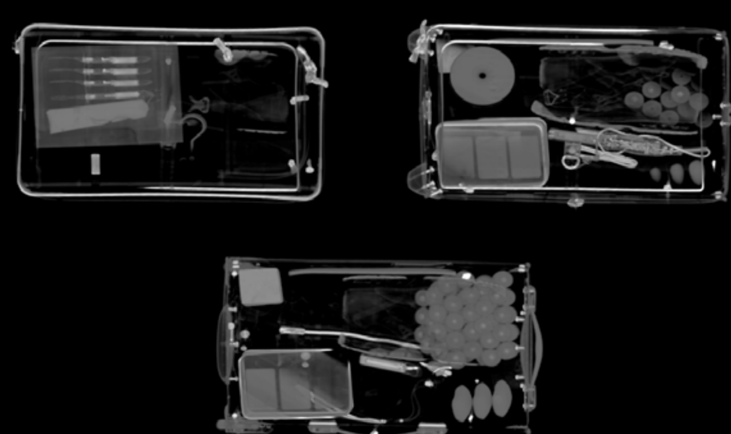
Object Merging

- We merge objects based on the following three criteria
  - Spatial proximity
    - Objects within some distance from the boundary
  - Mean MHU values
  - Type of objects (bulk, medium thickness, sheet)
    - Represented by a mean of distance transform of binary masks

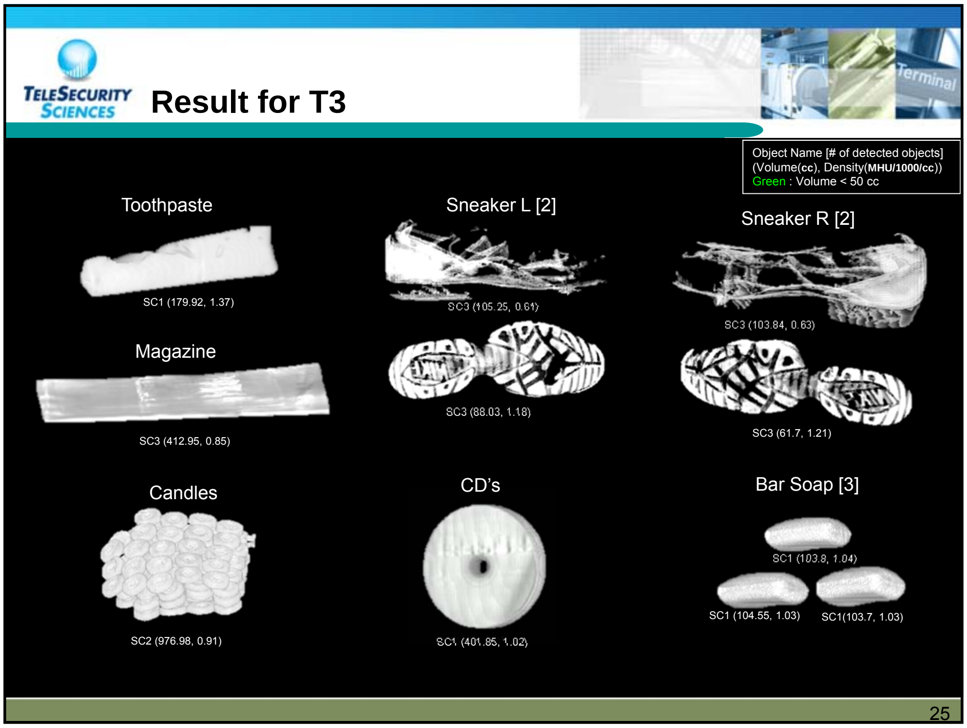


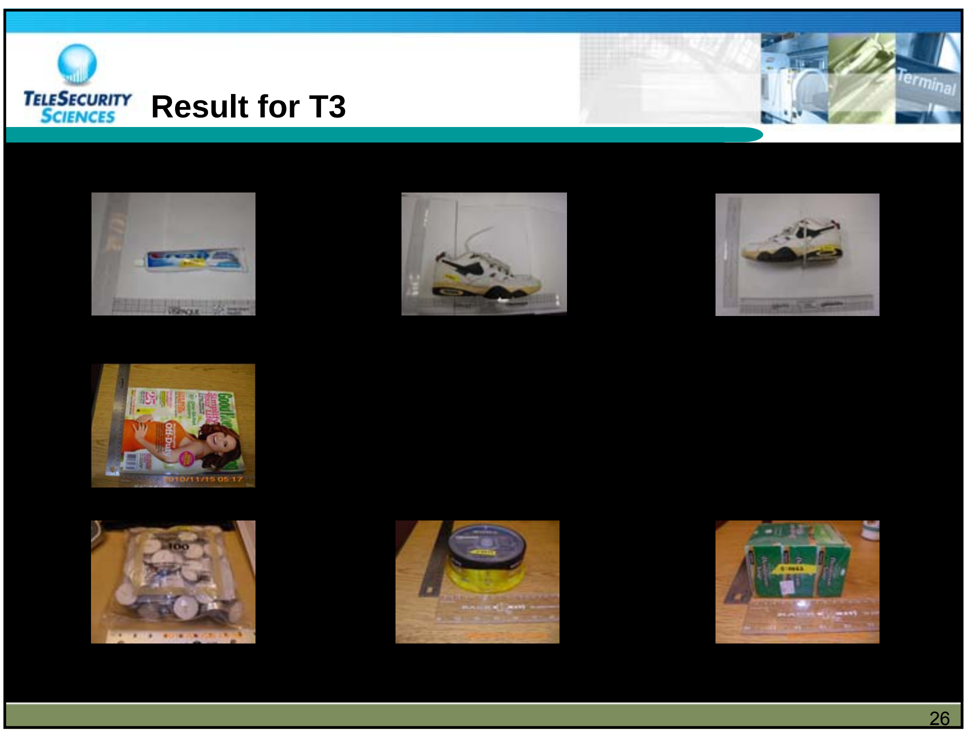
23

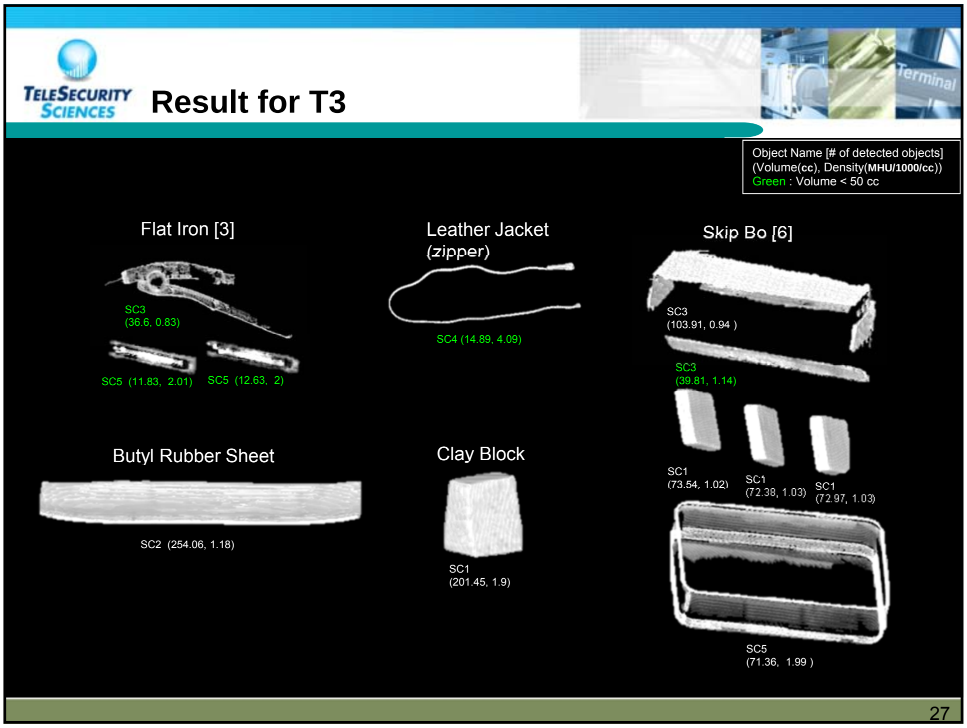
Dataset T3

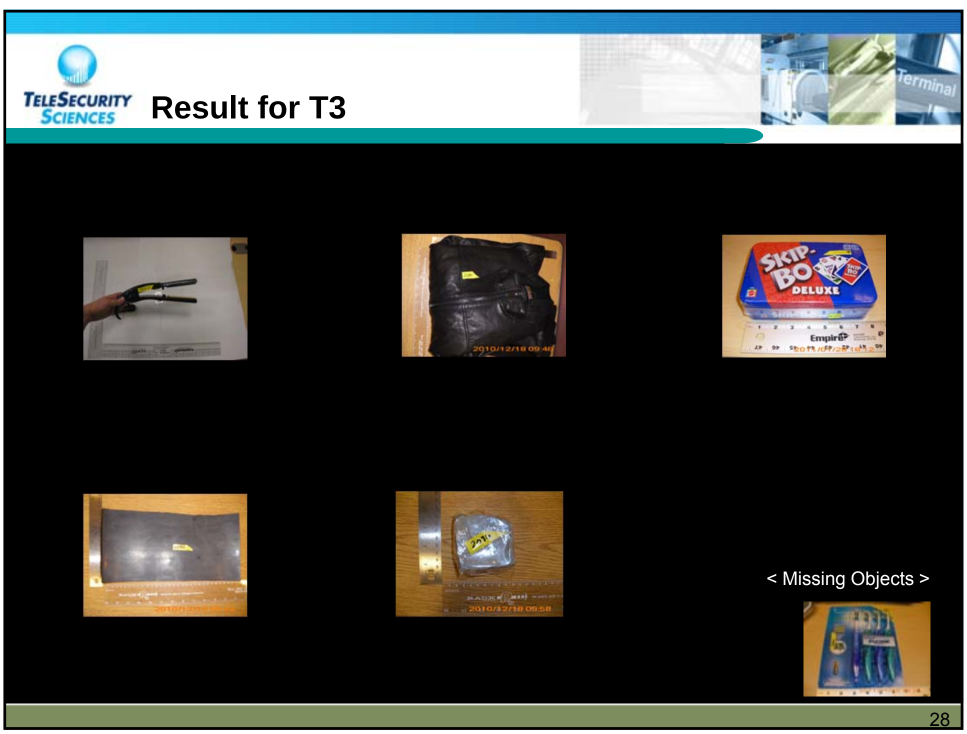


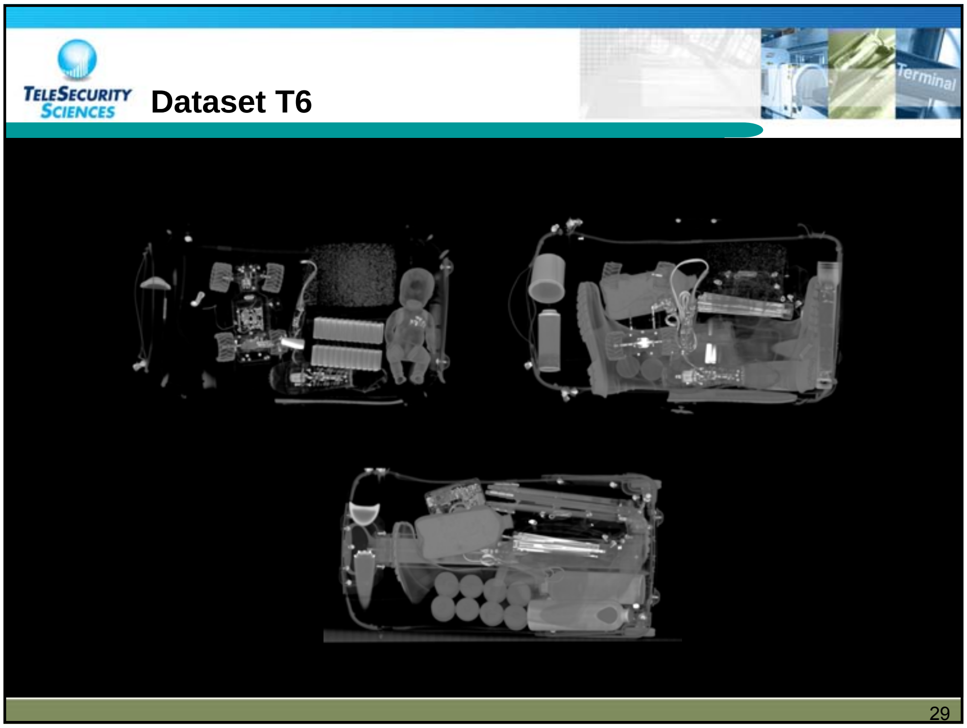
24

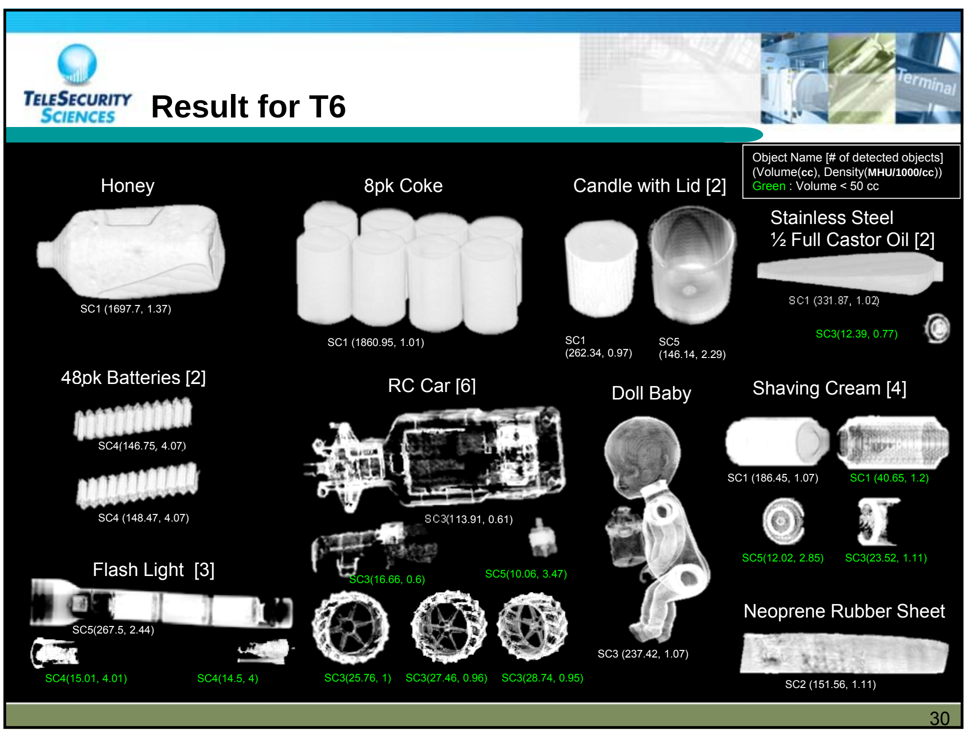

Result for T3
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Toothpaste
SC1 (179.92, 1.37)
Magazine
SC3 (412.95, 0.85)
Sneaker L [2]
SC3 (105.25, 0.61)
SC3 (88.03, 1.18)
Sneaker R [2]
SC3 (103.84, 0.63)
SC3 (61.7, 1.21)
Candles
SC2 (976.98, 0.91)
CD's
SC1 (401.85, 1.02)
Bar Soap [3]
SC1 (103.8, 1.04)
SC1 (104.55, 1.03)
SC1(103.7, 1.03)
25


Result for T3
26

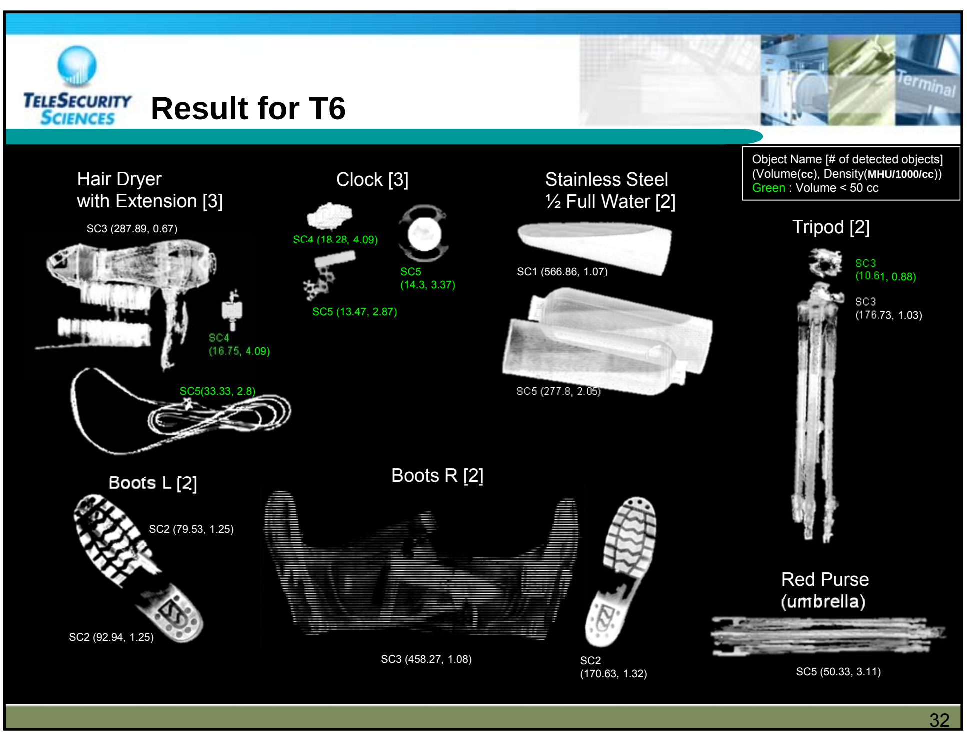

TeleSecurity Sciences
Result for T3
Terminal
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Flat Iron [3]
SC3
(36.6, 0.83)
SC5 (11.83, 2.01)
SC5 (12.63, 2)
Leather Jacket
(zipper)
SC4 (14.89, 4.09)
Skip Bo [6]
SC3
(103.91, 0.94)
SC3
(39.81, 1.14)
SC1
(73.54, 1.02)
SC1
(72.38, 1.03)
SC1
(72.97, 1.03)
SC5
(71.36, 1.99)
Butyl Rubber Sheet
SC2 (254.06, 1.18)
Clay Block
SC1
(201.45, 1.9)
27


TeleSecurity Sciences
Result for T3
Terminal
SKIP-BO
DELUXE
< Missing Objects >
28


TeleSecurity Sciences
Dataset T6
29


TeleSecurity Sciences
Result for T6
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Honey
SC1 (1697.7, 1.37)
8pk Coke
SC1 (1860.95, 1.01)
Candle with Lid [2]
SC1
(262.34, 0.97)
SC5
(146.14, 2.29)
Stainless Steel
½ Full Castor Oil [2]
SC1 (331.87, 1.02)
SC3(12.39, 0.77)
48pk Batteries [2]
SC4(146.75, 4.07)
SC4 (148.47, 4.07)
RC Car [6]
SC3(113.91, 0.61)
SC3(16.66, 0.6)
SC5(10.06, 3.47)
SC3(25.76, 1)
SC3(27.46, 0.96)
SC3(28.74, 0.95)
Doll Baby
SC3 (237.42, 1.07)
Shaving Cream [4]
SC1 (186.45, 1.07)
SC1 (40.65, 1.2)
SC5(12.02, 2.85)
SC3(23.52, 1.11)
Flash Light [3]
SC5(267.5, 2.44)
SC4(15.01, 4.01)
SC4(14.5, 4)
Neoprene Rubber Sheet
SC2 (151.56, 1.11)
30


TeleSecurity Sciences
Result for T6
Terminal
31


TeleSecurity Sciences
Result for T6
Terminal
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Hair Dryer
with Extension [3]
SC3 (287.89, 0.67)
SC4
(16.75, 4.09)
SC5(33.33, 2.8)
Clock [3]
SC4 (18.28, 4.09)
SC5
(14.3, 3.37)
SC5 (13.47, 2.87)
Stainless Steel
½ Full Water [2]
SC1 (566.86, 1.07)
SC5 (277.8, 2.05)
Tripod [2]
SC3
(10.61, 0.88)
SC3
(176.73, 1.03)
Boots L [2]
SC2 (79.53, 1.25)
SC2 (92.94, 1.25)
Boots R [2]
SC3 (458.27, 1.08)
SC2
(170.63, 1.32)
Red Purse
(umbrella)
SC5 (50.33, 3.11)
32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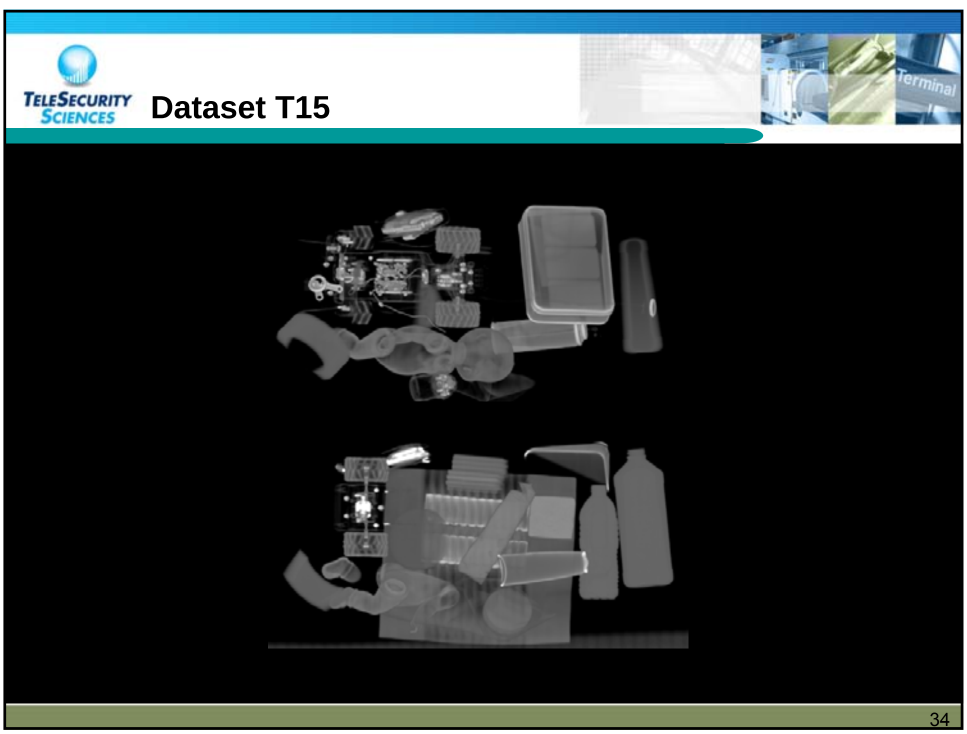
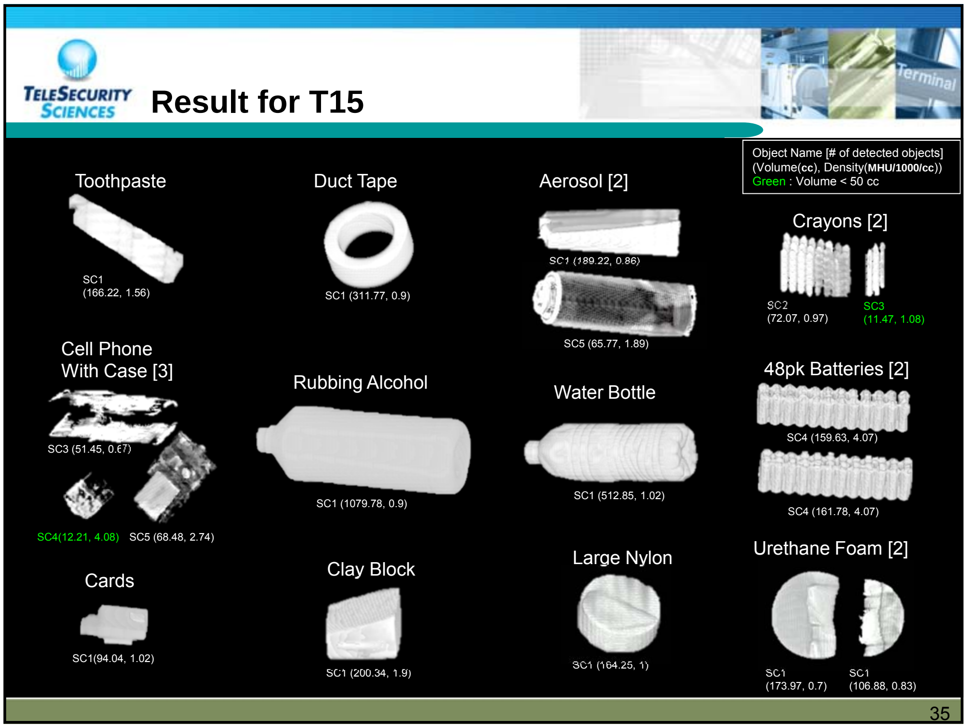
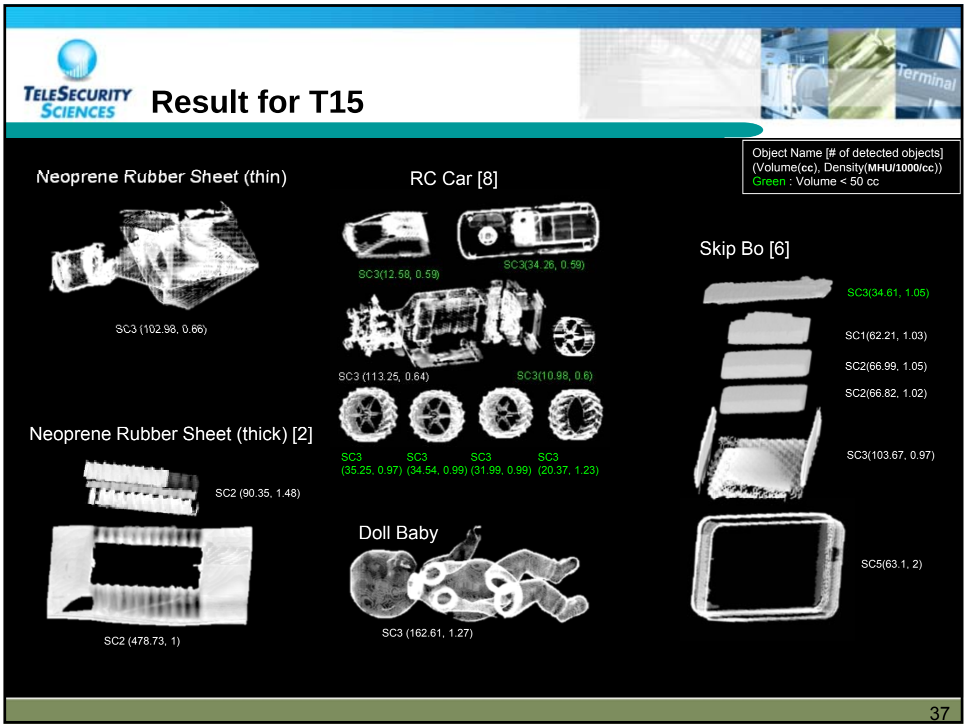
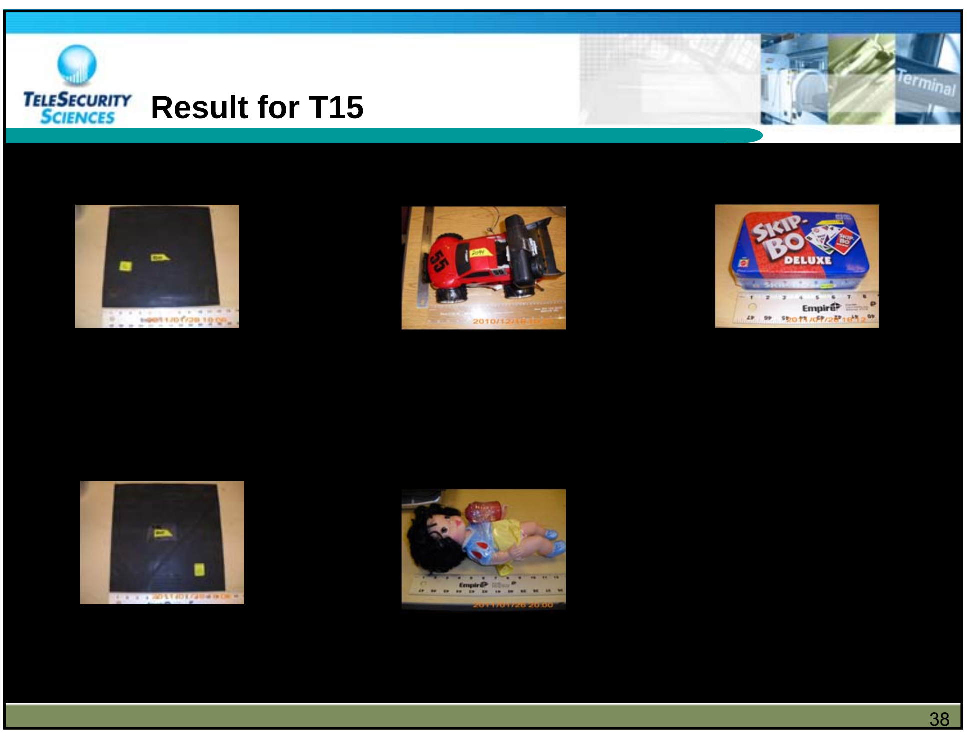
Result for T6
33

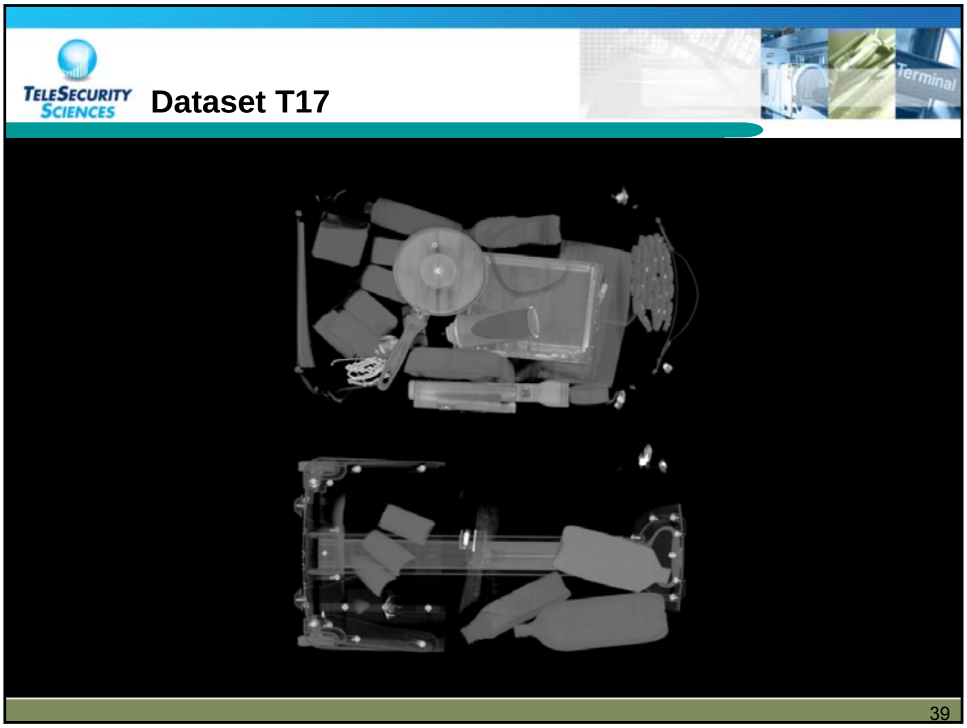

TeleSecurity Sciences
Dataset T15
34

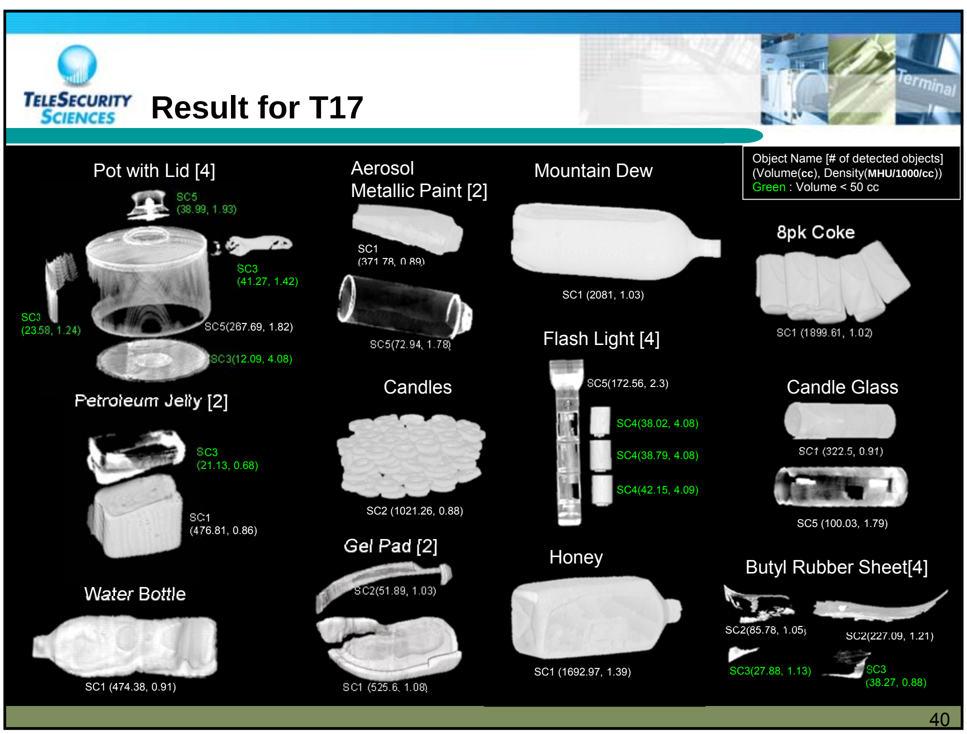

TeleSecurity Sciences
Result for T15
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Toothpaste
SC1
(166.22, 1.56)
Duct Tape
SC1 (311.77, 0.9)
Aerosol [2]
SC1 (189.22, 0.86)
SC5 (65.77, 1.89)
Crayons [2]
SC2
(72.07, 0.97)
SC3
(11.47, 1.08)
Cell Phone
With Case [3]
SC3 (51.45, 0.67)
SC4(12.21, 4.08)
SC5 (68.48, 2.74)
Rubbing Alcohol
SC1 (1079.78, 0.9)
Water Bottle
SC1 (512.85, 1.02)
48pk Batteries [2]
SC4 (159.63, 4.07)
SC4 (161.78, 4.07)
Cards
SC1(94.04, 1.02)
Clay Block
SC1 (200.34, 1.9)
Large Nylon
SC1 (164.25, 1)
Urethane Foam [2]
SC1
(173.97, 0.7)
SC1
(106.88, 0.83)
35

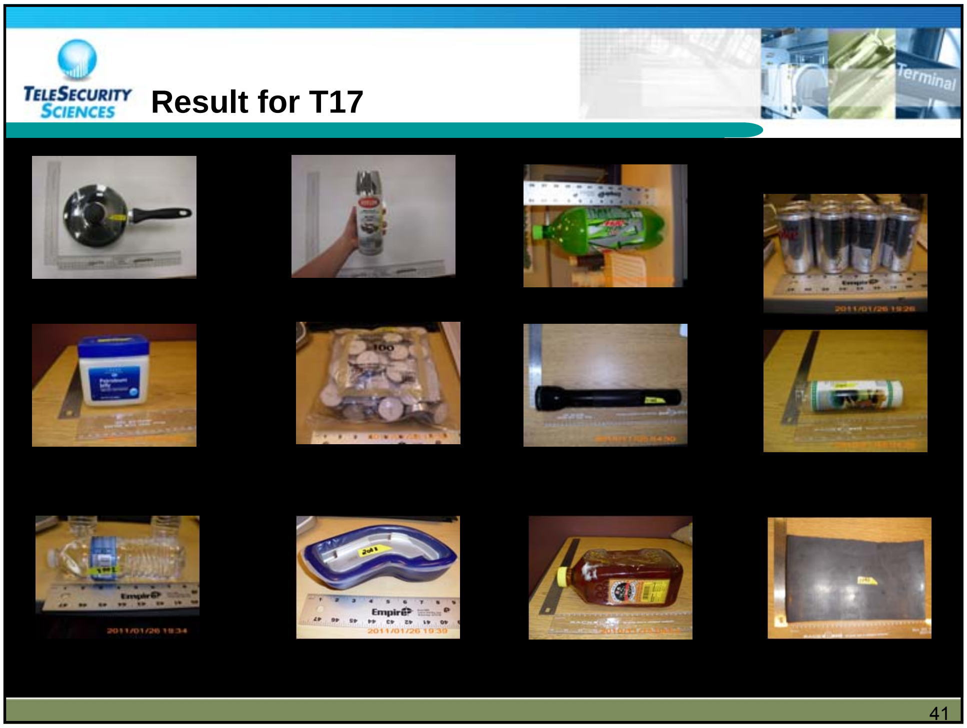

TeleSecurity Sciences
Result for T15
36

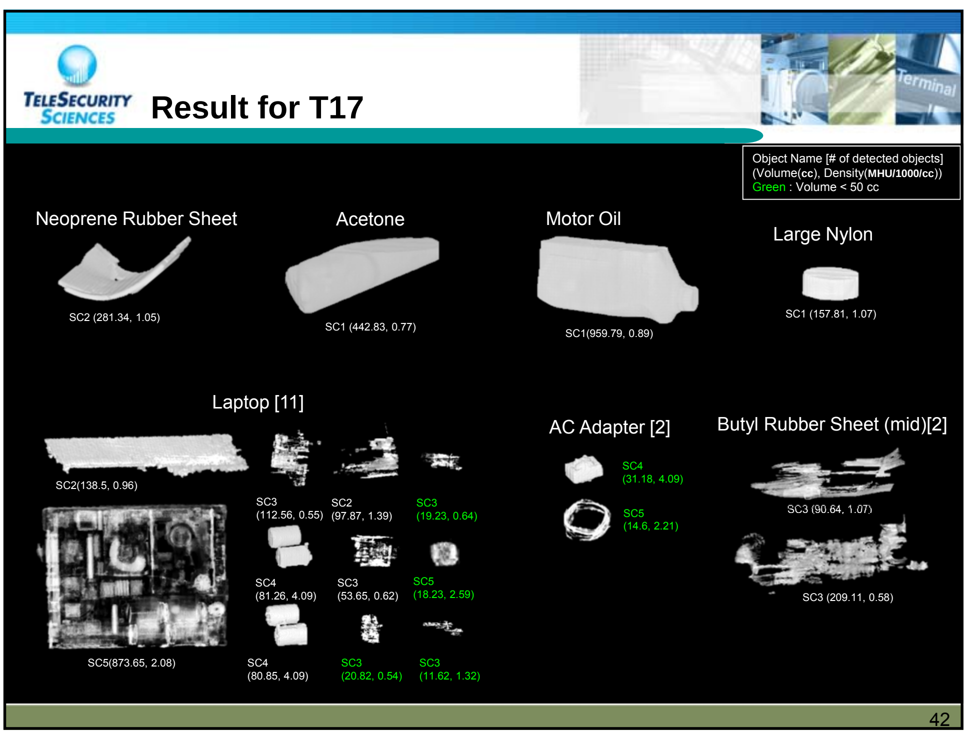

TeleSecurity Sciences
Result for T15
Terminal
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Neoprene Rubber Sheet (thin)
SC3 (102.98, 0.66)
Neoprene Rubber Sheet (thick) [2]
SC2 (90.35, 1.48)
SC2 (478.73, 1)
RC Car [8]
SC3(12.58, 0.59)
SC3(34.26, 0.59)
SC3 (113.25, 0.64)
SC3(10.98, 0.6)
SC3 (35.25, 0.97)
SC3 (34.54, 0.99)
SC3 (31.99, 0.99)
SC3 (20.37, 1.23)
Doll Baby
SC3 (162.61, 1.27)
Skip Bo [6]
SC3(34.61, 1.05)
SC1(62.21, 1.03)
SC2(66.99, 1.05)
SC2(66.82, 1.02)
SC3(103.67, 0.97)
SC5(63.1, 2)
37


TeleSecurity Sciences
Result for T15
Terminal
SKIP-BO
DELUXE
38


TeleSecurity Sciences
Dataset T17
Terminal
39


TeleSecurity Sciences
Result for T17
Terminal
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Pot with Lid [4]
SC5
(38.99, 1.93)
SC3
(41.27, 1.42)
SC3
(23.58, 1.24)
SC5(267.69, 1.82)
SC3(12.09, 4.08)
Aerosol
Metallic Paint [2]
SC1
(371.78, 0.89)
SC5(72.94, 1.78)
Mountain Dew
SC1 (2081, 1.03)
8pk Coke
SC1 (1899.61, 1.02)
Petroleum Jelly [2]
SC3
(21.13, 0.68)
SC1
(476.81, 0.86)
Candles
SC2 (1021.26, 0.88)
Flash Light [4]
SC5(172.56, 2.3)
SC4(38.02, 4.08)
SC4(38.79, 4.08)
SC4(42.15, 4.09)
Candle Glass
SC1 (322.5, 0.91)
SC5 (100.03, 1.79)
Water Bottle
SC1 (474.38, 0.91)
Gel Pad [2]
SC2(51.89, 1.03)
SC1 (525.6, 1.08)
Honey
SC1 (1692.97, 1.39)
Butyl Rubber Sheet[4]
SC2(85.78, 1.05)
SC2(227.09, 1.21)
SC3(27.88, 1.13)
SC3
(38.27, 0.88)
40

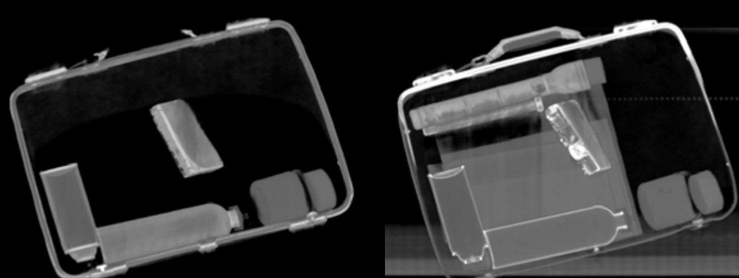

TeleSecurity Sciences
Result for T17
Terminal
41


TeleSecurity Sciences
Result for T17
Terminal
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Neoprene Rubber Sheet
SC2 (281.34, 1.05)
Acetone
SC1 (442.83, 0.77)
Motor Oil
SC1(959.79, 0.89)
Large Nylon
SC1 (157.81, 1.07)
Laptop [11]
SC2(138.5, 0.96)
SC5(873.65, 2.08)
SC3 (112.56, 0.55)
SC2 (97.87, 1.39)
SC3 (19.23, 0.64)
SC4 (81.26, 4.09)
SC3 (53.65, 0.62)
SC5 (18.23, 2.59)
SC4 (80.85, 4.09)
SC3 (20.82, 0.54)
SC3 (11.62, 1.32)
AC Adapter [2]
SC4 (31.18, 4.09)
SC5 (14.6, 2.21)
Butyl Rubber Sheet (mid)[2]
SC3 (90.64, 1.07)
SC3 (209.11, 0.58)
42

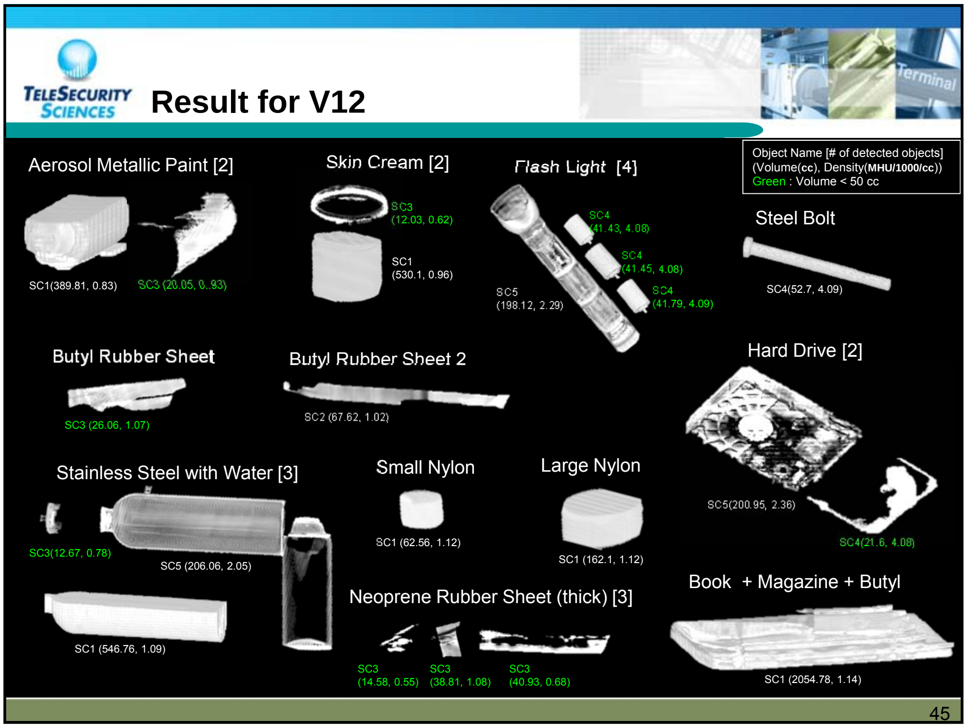
Result for T17

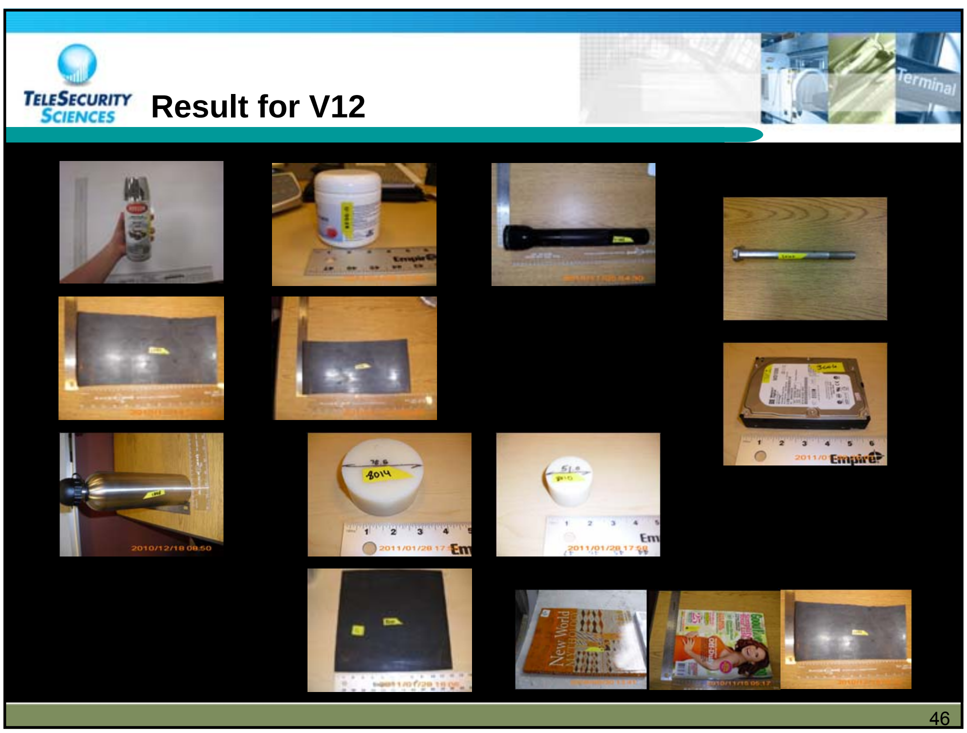
43

Dataset V12



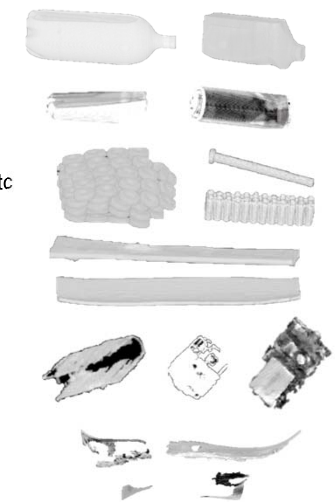
44


TeleSecurity Sciences
Result for V12
Terminal
Aerosol Metallic Paint [2]
SC1(389.81, 0.83)
SC3 (20.05, 0.93)
Skin Cream [2]
SC3
(12.03, 0.62)
SC1
(530.1, 0.96)
Flash Light [4]
SC4
(41.43, 4.08)
SC4
(41.45, 4.08)
SC4
(41.79, 4.09)
SC5
(198.12, 2.29)
Object Name [# of detected objects]
(Volume(cc), Density(MHU/1000/cc))
Green : Volume < 50 cc
Steel Bolt
SC4(52.7, 4.09)
Butyl Rubber Sheet
SC3 (26.06, 1.07)
Butyl Rubber Sheet 2
SC2 (67.62, 1.02)
Hard Drive [2]
SC5(200.95, 2.36)
SC4(21.6, 4.08)
Stainless Steel with Water [3]
SC3(12.67, 0.78)
SC5 (206.06, 2.05)
SC1 (546.76, 1.09)
Small Nylon
SC1 (62.56, 1.12)
Large Nylon
SC1 (162.1, 1.12)
Neoprene Rubber Sheet (thick) [3]
SC3
(14.58, 0.55)
SC3
(38.81, 1.08)
SC3
(40.93, 0.68)
Book + Magazine + Butyl
SC1 (2054.78, 1.14)
45


TeleSecurity Sciences
Result for V12
Terminal
46

Overall Performance

- Performs well for homogeneous objects such as
  - Bulk objects
    - Bottles of liquid
      - Water, beverage, honey, oil, aerosol, etc
      - Steel bottles are segmented separately.
    - Clay block, nylon, candle, piece of steel, battery, etc
  - Medium thickness objects (5-10 voxels thick)
    - Magazine, thick rubber sheet, etc
- Performs well for heterogeneous objects
  - Ex) Cell phone → leather case + inner metallic part + remaining heterogeneous part
- All sheet objects are segmented but
  - Usually segmented in several smaller pieces for thin rubber sheets
- Misses very small metallic objects.



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Limitations

- Thin rubber sheets are segmented as several smaller pieces.
  - MHU values of thin rubber sheets are spread over from 0 to 600-800 across 7-10 voxels
  - In SC3, by thresholding with $I_1 = 400, I_2 = 1500$, the binary mask for thin rubber sheets are 2-3 voxel wide.
  - In some cases, the mask becomes 1 or 0 pixel width because of streaking CT artifacts ➔ Objects are split into several smaller pieces
  - Partial volume compensation processing is needed
    - The scanner appears to have the PSF with FWHM of about 3-4 mm
    - A 3mm sheet shows up as a sheet of about 6 voxels FWHM with MHU of ~600
- Fails to segment the stack of sheet objects in V12 correctly.
  - We segmented it as a single large bulk object as all sheets have similar MHU.
- We have conceptual solutions to solve these limitations. Additional effort will be required to implement the solutions with additional funding.

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Feature Extraction

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- Mass-CT
  - Mass of object (Units: MHU / 1000 x voxel size)
    = Sum of Object CT value x 0.001 x (0.98x0.98x1.29) x 0.001
- Volume
  - Volume of object (Units: cc)
    = Number of voxels in object x (0.98x0.98x1.29) x 0.001
- Density-CT
  - Mass-CT / Volume
- Std-CT
  - Standard deviation of Object CT values`
- Alarm Decision:
  - Density, Volume, Confidence (Std-CT, Number of Voxels, etc.)

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Comparison with Reference– Minimum Volume: 50 cc

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Percent Overlap Between Detected Objects and Ground Truth

Dataset T3		Dataset T6		Dataset T15		Dataset T17		Dataset V12	
Toothpaste tube	93.03	Honey	95.16	Toothpaste tube	84.18	Pot with lid	28.12	Aerosol-metallic paint	76.98
Sneaker – R	16.31	Clock with cord	23.78	Duct tape	94.61	Aerosol -metallic paint	77.79	Skin Cream	90.77
Sneaker – L	17.24	Red purse	7.61	Crayons	24.77	2Liter MtnDew	95.33	Large Flashlight	42.48
Flat Iron	0.00	Hair drier	21.86	Aerosol Off!	70.46	8pk soda	89.80	Steel bolt	96.59
CD's	78.30	Boots-R	51.61	Cell phone	47.57	Petroleum jelly	88.00	Butyl Rubber (thick)	76.29
Bar Soap	60.39	Boots-L	50.75	Water bottle	90.61	Tealite candles	78.27	Butyl Rubber (thick)	71.80
Candles	76.81	Camera Tripod	36.66	Block of Clay	91.82	Candle-glass	85.34	Hard Drive	64.94
Toothbrushes	3.16	Rubber (soft)	65.14	RC Car	7.83	Fashlight-large	27.54	Stainless Steel containing water	78.86
Leather Jacket	1.80	RC Car	14.80	Toy	32.88	Water bottle	90.56	Small Nylon cylinder	98.64
Rubber (harder)	87.84	Diet coke	89.38	Batteries - 48 pk	79.85	Gel pad	83.12	Large Nylon Cylinder	100.00
Magazine - GH	89.05	Candle with lid	89.38	Rubbing Alcohol	93.88	Honey	90.72	Neoprene (thick)	73.16
Skip Bo	55.42	Stainless Steel 1/2 Full water	85.92	Playing cards – 2	74.45	Butyl Rubber (thick)	41.00	Magazine -GH	95.99
		Stainless Steel 1/2 Full Castor oil	69.52	Large Nylon	95.85	Neoprene (thick)	59.86	High Clay book	100.00
		Doll	46.60	Urethane foam	91.83	Acetone	85.75		
		Batteries	79.67	Neoprene (thin)	34.06	Motor oil -2	83.70		
		Edge shaving cream	60.11	Neoprene (thick)	63.63	AC adapter – Grey	0.52		
		Large Flashlight	63.51	Skip B0	41.53	Laptop	53.79		
						Large Nylon	93.98		
						Butyl rubber (mid)	21.59		

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Comparison with Reference– Minimum Volume: 10 cc

Percent Overlap Between Detected Objects and Ground Truth

Dataset T3		Dataset T6		Dataset T15		Dataset T17		Dataset V12	
Toothpaste tube	93.03	Honey	95.16	Toothpaste tube	86.52	Pot with lid	39.44	Aerosol-metallic paint	80.64
Sneaker – R	25.36	Clock with cord	25.49	Duct tape	94.61	Aerosol -metallic paint	78.09	Skin Cream	92.73
Sneaker – L	17.24	Red purse	8.58	Crayons	28.32	2Liter MtnDew	95.33	Large Flashlight	78.65
Flat Iron	26.48	Hair drier	29.66	Aerosol Off!	72.32	8pk soda	89.80	Steel bolt	96.59
CD's	78.30	Boots-R	51.61	Cell phone	52.43	Petroleum jelly	89.80	Butyl Rubber (thick)	83.34
Bar Soap	60.39	Boots-L	50.95	Water bottle	90.61	Tealite candles	78.27	Butyl Rubber (thick)	73.39
Candles	76.81	Camera Tripod	38.68	Block of Clay	91.82	Candle-glass	85.75	Hard Drive	76.33
Toothbrushes	3.16	Rubber (soft)	65.14	RC Car	19.67	Fashlight-large	54.73	Stainless Steel containing water	80.27
Leather Jacket	2.45	RC Car	21.53	Toy	32.91	Water bottle	90.59	Small Nylon cylinder	98.64
Rubber (harder)	87.84	Diet coke	89.38	Batteries - 48 pk	87.74	Gel pad	83.25	Large Nylon Cylinder	100.00
Magazine - GH	90.16	Candle with lid	89.38	Rubbing Alcohol	93.88	Honey	90.72	Neoprene (thick)	85.28
Skip Bo	61.87	Stainless Steel 1/2 Full water	85.92	Playing cards – 2	83.74	Butyl Rubber (thick)	44.80	Magazine -GH	96.02
		Stainless Steel 1/2 Full Castor oil	71.33	Large Nylon	95.85	Neoprene (thick)	61.01	High Clay book	100.00
		Doll	46.60	Urethane foam	92.53	Acetone	85.75		
		Batteries	87.04	Neoprene (thin)	35.38	Motor oil -2	83.70		
		Edge shaving cream	77.92	Neoprene (thick)	65.16	AC adapter – Grey	24.46		
		Large Flashlight	73.04	Skip B0	45.70	Laptop	57.31		
						Large Nylon	93.98		
						Butyl rubber (mid)	22.17		

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Detection Performance

Number of Detected Objects

		Dataset T3			Dataset T6			Dataset T15			Dataset T17			Dataset V12		
Total Number of Objects		12			17			17			19			13		
		Intersection (%)														
		10	30	50	10	30	50	10	30	50	10	30	50	10	30	50
Volume (cc)	10	10	7	7	16	13	11	17	15	12	19	17	15	13	13	13
	20	10	7	7	16	13	11	17	15	11	19	17	15	13	13	13
	30	10	7	7	16	13	11	17	15	11	19	17	15	13	13	13
	40	9	7	7	16	13	11	16	15	11	18	17	14	13	13	13
	50	9	7	7	16	13	11	16	15	11	18	15	14	13	13	12

$$PD = \frac{\text{Number of Detected Objects}}{\text{Total Number of Objects}}$$

Volume (cc)	10			20			30			40			50		
Intersection (%)	10	30	50	10	30	50	10	30	50	10	30	50	10	30	50
PD	0.962	0.833	0.744	0.962	0.833	0.731	0.962	0.833	0.73	0.923	0.833	0.718	0.923	0.807	0.705

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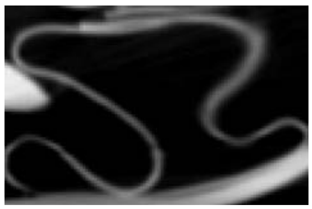
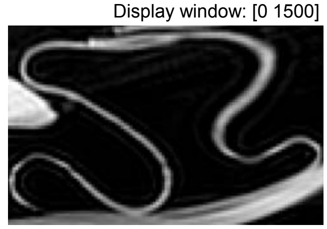
Work-in-Progress: Deconvolution for Sheets

- Deblurring by Wiener filtering using estimated blur kernels
  - Neoprene rubber sheet from T15

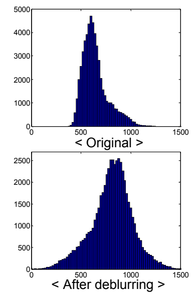
Display window: [0 1500]



< Original >



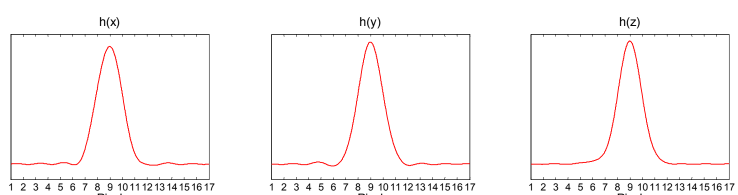
< After deblurring>



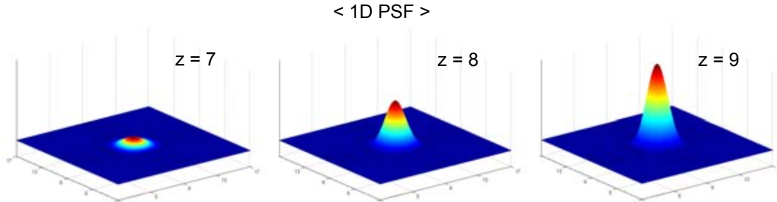
  - Density of segmented sheet from original image: 0.662
  - Density of segmented sheet from deblurred image: 0.811
  - After the “maximum filtering”: 1.05
    - Density of Neoprene: ~1.23 g/cc

Work-in-Progress: Deconvolution Kernel

- Blur kernels estimated from CT images



< 1D PSF >



< 3D PSF >

$h(x,y,z) = h(x)h(y)h(z)$

Strengths and Weaknesses

- Strengths: entire segmentation process consists of five sequential SCs focusing on objects with different characteristics
  - Fast implementation: each SC takes about 10 secs with current GPU implementation. Further optimization should result in sub-second processing.
  - The algorithm can adapt to emerging threats by tuning the SC parameters
  - Upon detection of all objects, advanced high-level processing (AI) can be added
    - For instance, bulk/sheet → detonator → conductor → power source ➔ THREAT
- Weaknesses
  - Fails to segment the stack of sheet objects in V12 correctly.
  - Misses very small metallic objects that are inner parts of heterogeneous objects (volume constraint)

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Risks and Mitigation

- Risks
  - The proposed approach has only been tested on a limited set of data. It may perform poorly on other data.
  - As in all other detection systems, the system will never achieve PD = 100%.
- Mitigation
  - Collect and process more data, develop more specific algorithms, perform additional testing.
  - Tightly integrate ATD output with the Level 2 workstation and OSARP (HR-OSARP).
    - Provide exquisite 3-D renderings (Electronic Unpacking) of objects in bags.
    - Allow screeners to flag regions not flagged by the ATD.

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Comments

- Reference labels (ground truths) should respect homogeneity.
  - The reference label for the stainless steel bottle with water includes both the bottle and water.
  - Cell phone …, Notebook Computer …
- The thickness measurements for sheets.
  - Would have allowed checking of partial volume compensation processing, e.g., deconvolution processing
- Further work towards ATD for EDS
  - Need good luggage detector (external casing)
  - Need to recognize metal, wire, circuit boards, and batteries
    - Artificial intelligence, heuristics, etc.

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Recommendation

- To ALERT
  - Evolve the challenge: CT Segmentation → ATD for EDS
    - More data from real EDS with real threats (IEDS, sheets, etc.)
    - The funding should match the budget required
- To DHS S&T and TSA
  - The results warrant further funding to develop the ideas further
  - Perhaps a RFP?
  - EDS Certification Process to deploy best-of-the-best system
    - DICOS Standard will support the separation of EDS Scanner and ATD Algorithm
    - Separate certification of EDS Scanner and ATD algorithm?
      - EDS Scanner: IQ, resolution, noise statistics, penetration, etc.
      - ATD Algorithm: ROC curve
    - TSS is a key partner of TASC for a recent TSA contract
      - ***Development of GUI for EDS (deliverable: Next Generation EDS Workstation)***
      - The Workstation may serve as a platform for all future ATD development

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9.1.6 "SIEVESECT," Richard Harvey, Paul Southam and Graham Tattersall, University of East Anglia

University of East Anglia

SIEVESECT

Richard Harvey, Paul Southam, Graham Tattersall

School of Computing Sciences
University of East Anglia,
Norwich, NR4 7TJ, UK

Executive summary

University of East Anglia

Novel scale-based technique

Sieve identifies potential objects (or segments) by region-growing from intensity extrema. Produced dense set of regions

Regions merged

Via density histogram comparison

Resulting regions are suited to further classification

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University of East Anglia
School of Computing Sciences

About UEA

- Well ranked
  - Guardian UK 18th
  - THES World rank 145
- Strong international brand
  - Sites in Norwich and London
  - Around 15000 students
- Lots of science
  - Europe's largest collection of bioscientists
  - New Scientist science rank – fourth in UK

University of East Anglia
School of Computing Sciences

About Computing Sciences

- Research intensive department
- Strong computer vision and signal processing presence
- Commercial activity via our consulting computing SYS Consulting Ltd
- Spin-out and IP-exploitation routes well established
- Access to our own venture funds (Iceni and LCIF)

Researchers

Richard Harvey, BSc PhD
Dean UEA London

Paul Southam, BSc PhD
Lead Researcher

Graham Tattersall, BSc PhD
Faculty member, CMP

200 peer-reviewed publications

Consultancy
- Security industry
- Government
- US Biotech
- Power

CMP Spin-outs
- Segmentis Ltd
- Fo2Pix Ltd
- Imsense Ltd
- Syrinix Ltd
- Urban Modelling Group
- Linguasign

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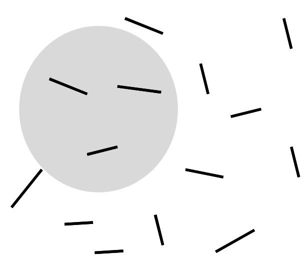
Problem Statement

To identify malignant objects in baggage:

Objects are *connected sets*…

that *contain* other connected sets.

Idea: decompose image into hierarchies of connected sets and extract features



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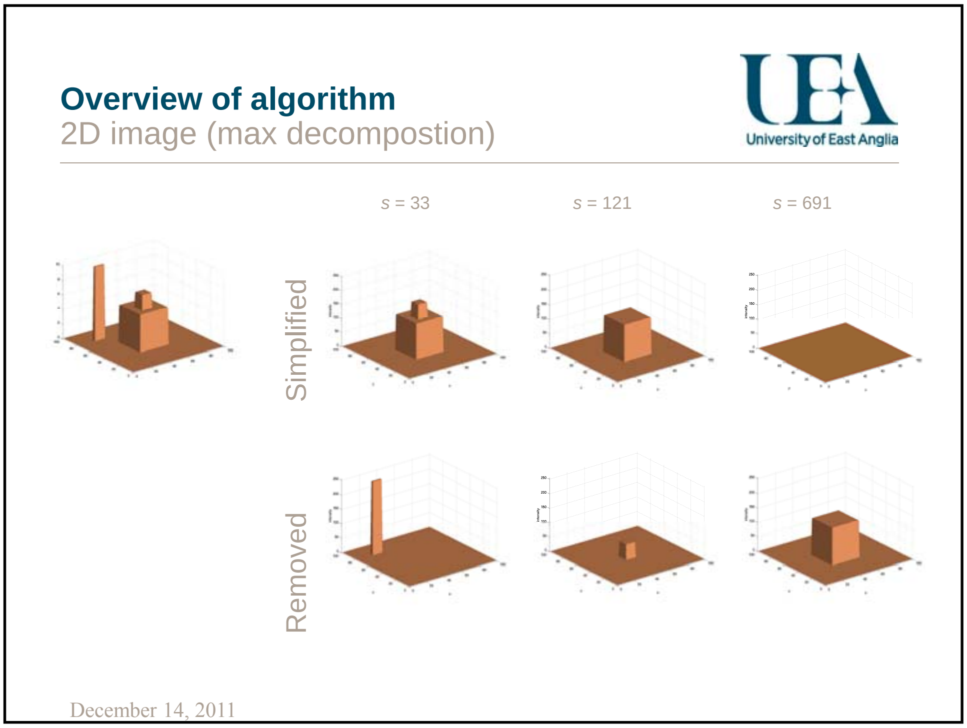
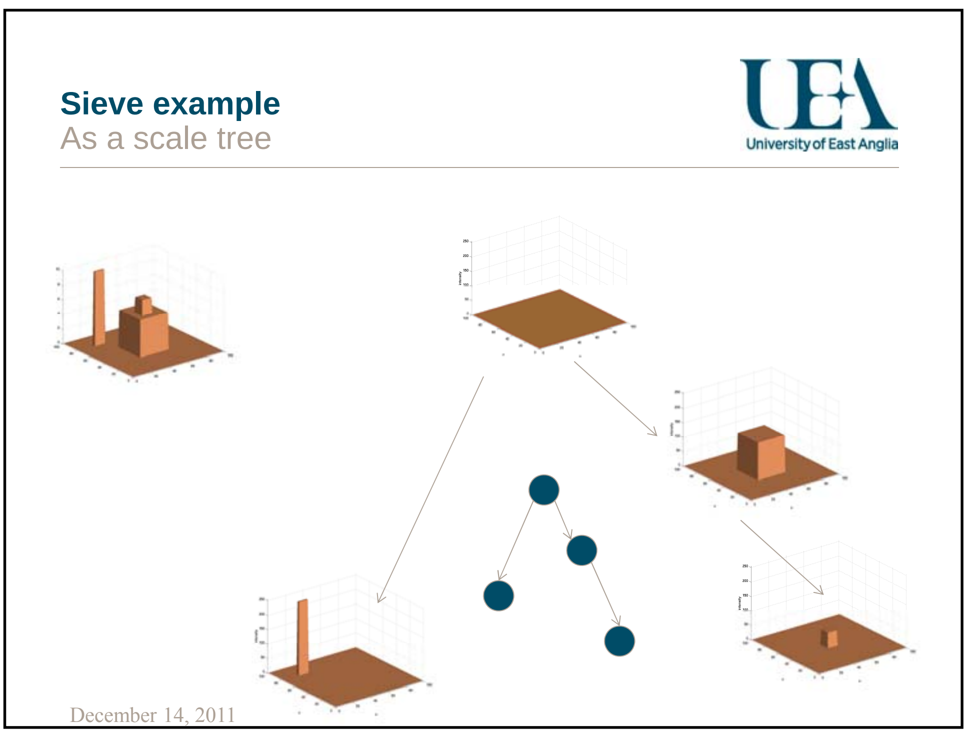

Overview of algorithm
2D image (max decompostion)
University of East Anglia
s = 33
s = 121
s = 691
Simplified
Removed
December 14, 2011


Sieve example
As a scale tree
University of East Anglia
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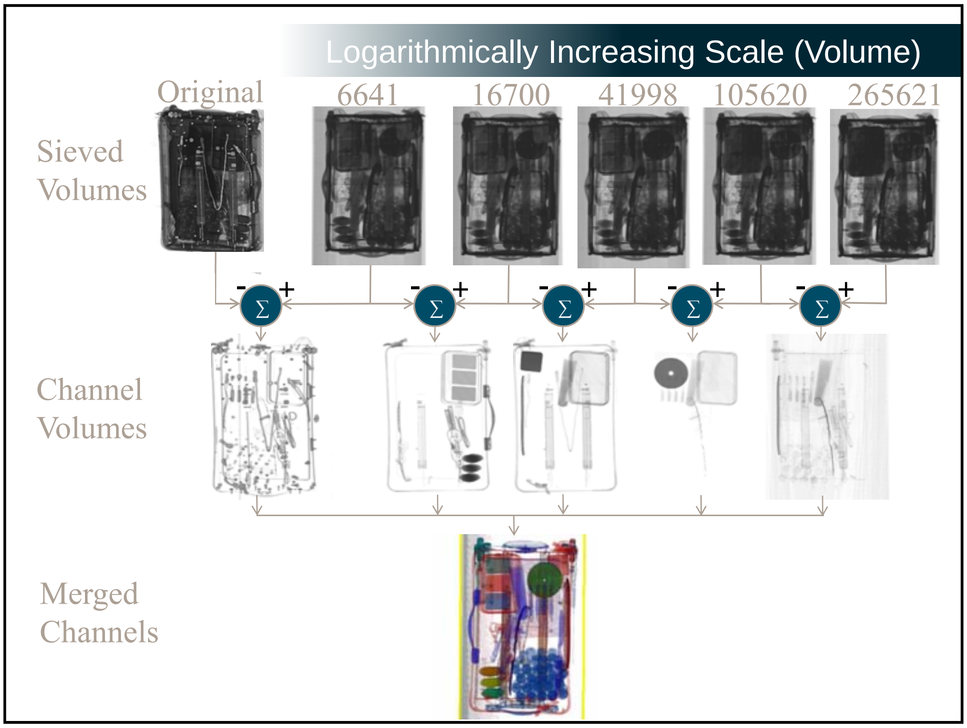
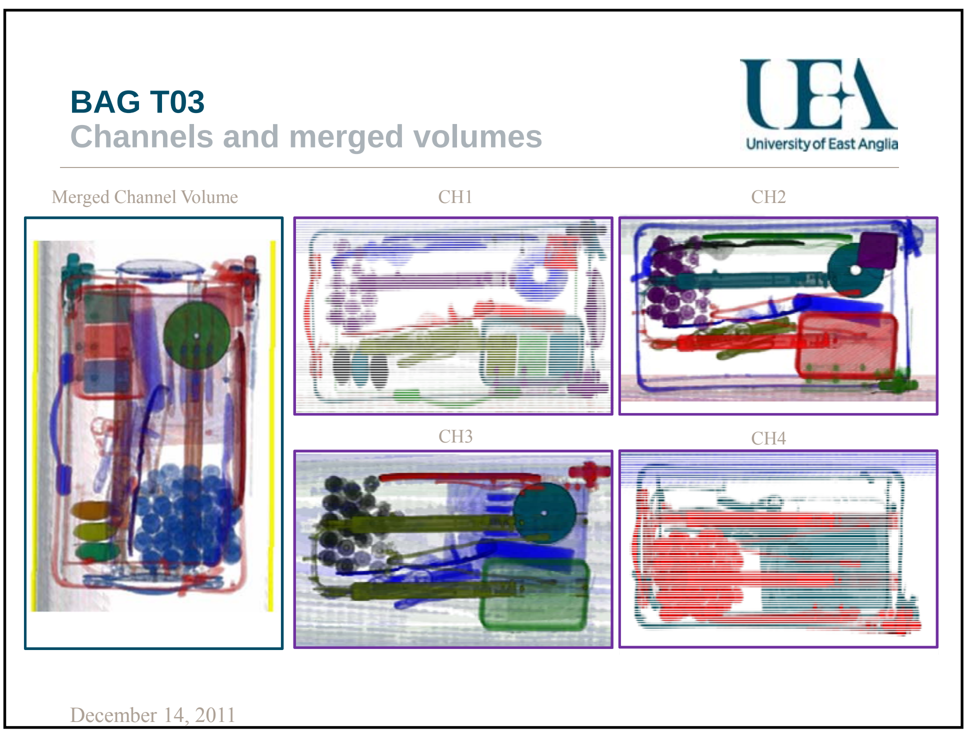

Logarithmically Increasing Scale (Volume)
Original
6641
16700
41998
105620
265621
Sieved Volumes
Channel Volumes
Merged Channels


BAG T03
Channels and merged volumes
University of East Anglia
Merged Channel Volume
CH1
CH2
CH3
CH4
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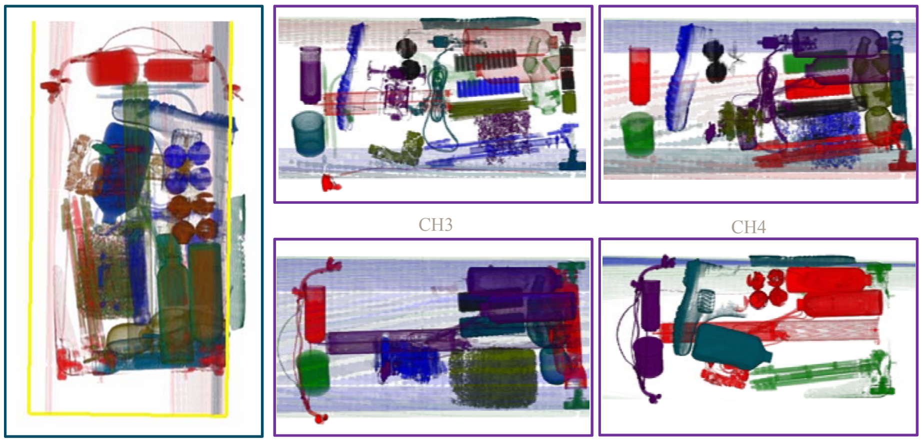
BAG T06
Channels and merged volumes

University of East Anglia



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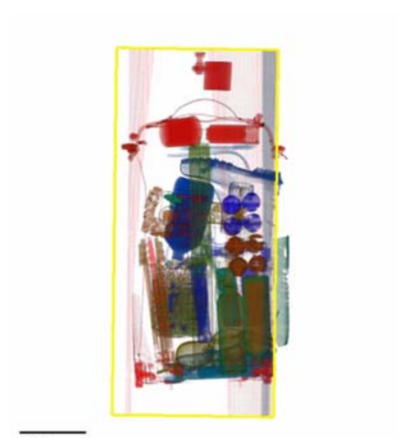
Segmentation Movies

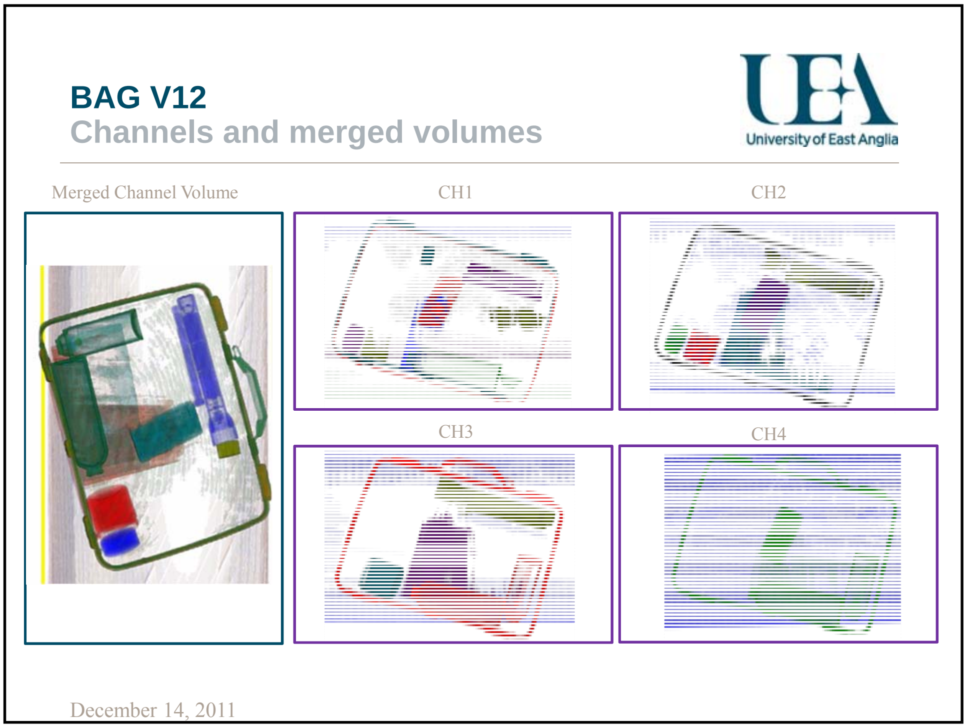
University of East Anglia

Bag 03



Bag 06

December 14, 2011


BAG V12
Channels and merged volumes
University of East Anglia
Merged Channel Volume
CH1
CH2
CH3
CH4
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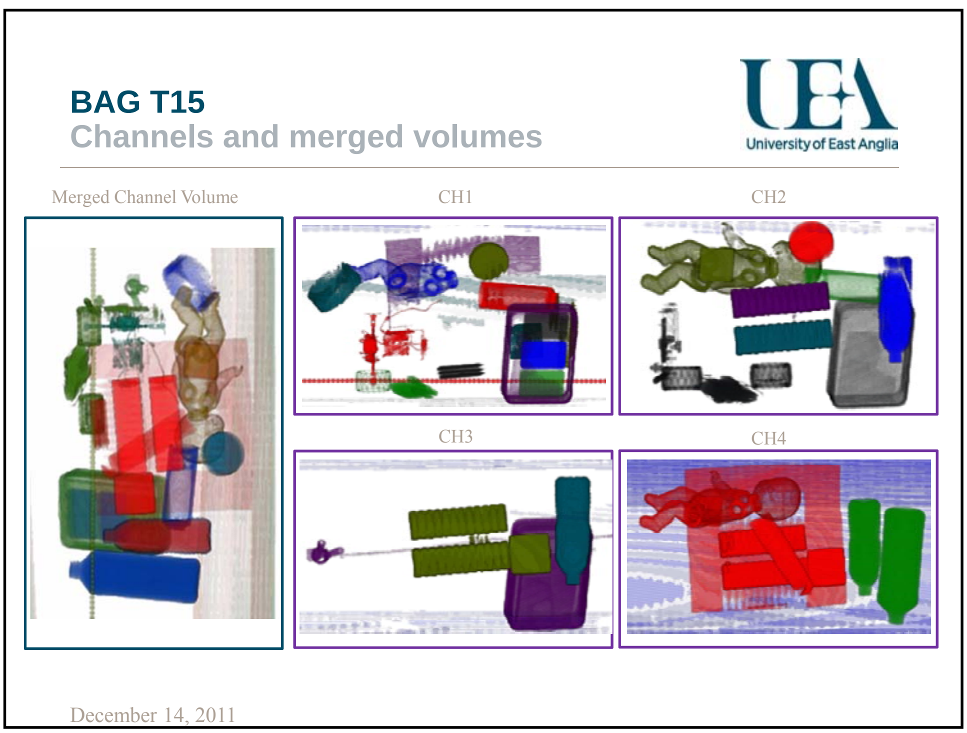
BAG T15
Channels and merged volumes
University of East Anglia
Merged Channel Volume
CH1
CH2
CH3
CH4
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Segmentation Movies

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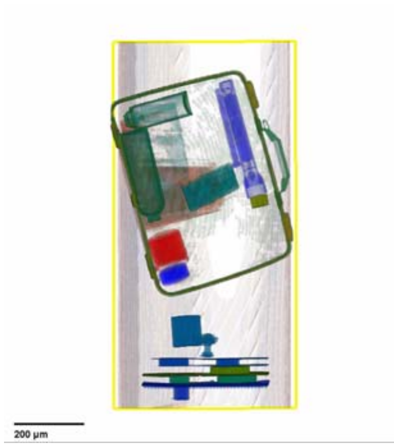

Bag 12

Bag 15

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Kolmogorov Smirnov Test

Parameter effects

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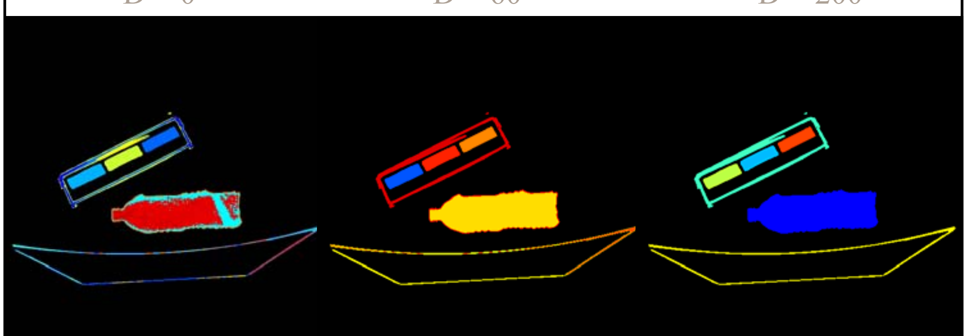
D = 0 D = 60 D = 200



Lan, Y., Harvey, R., Perez Torres, J.R., Finding Stable Salient Contours. In Image and Vision Computing, 28 (2010) p1244-1254.

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Kolmogorov Smirnov
Splitting/Merging

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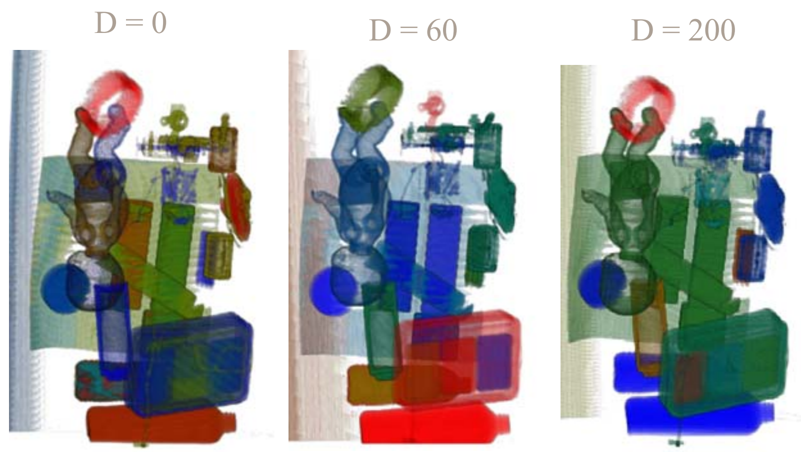

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CT artifacts

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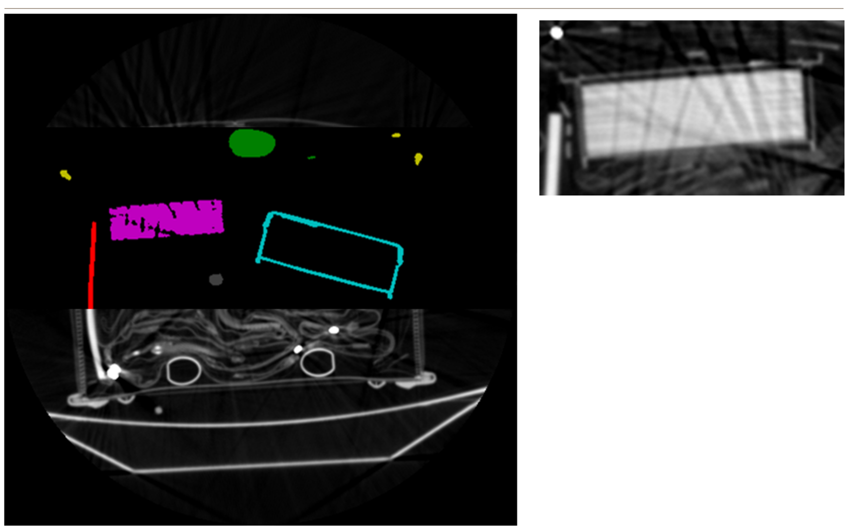

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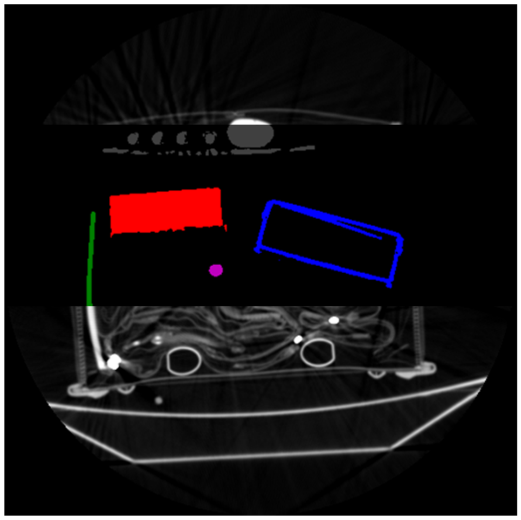
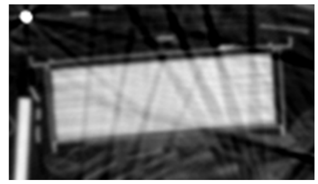
CT artifacts

University of East Anglia





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CT artifacts

Bag V12 Slice 462

Bag V12 Channel 2

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Limitations on types, densities, sizes, masses of objects that can be segmented

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- We are using density histograms to differentiate objects can be a problem if data are clipped.
- We *could* use shape/geometry.
- Subsequent to sieving we eliminate small-scale (50 ml) and large scale (2000 ml) objects.
- D not optimised via training.

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Feature Extraction for log files

University of East Anglia

- Our method returns regions that are statistically different from their parents – potential objects
- Density, volume and hence mass can be read directly from those regions – there is no post-processing of regions.

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Strength and Weaknesses

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Strengths

- Very general image transform.
- Covered by patents.
- Computationally efficient.
- Well proven scale-space robustness properties.
- Can be generalised to classification without segments (MSERs).

Weaknesses

- A transform is not the same as a classifier.
- Works on connected sets in the density domain.
  - Iso-density touching objects are not separable.
  - Non-cubic voxels need care.

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Risks and Mitigation

University of East Anglia

Technical Risks:

- Have we been working with representative data?
- Have we been solving a task that is representative of reality?
- Have we been solving a useful task?

Logistical Risks:

- Requires US-UK collaboration.
- Project is resourced out of the University.

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Comments

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- Much iteration on the ground truth data
- Huge commercial potential for supervised learning
- Sieves can be used in combination other with cool ideas
- For the future, it may be worth adopting more sophisticated methods for comparing segmentations
- Can avoid merging channels
  - Build classifier on channel data
  - Extend MSERs to 3D.

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Recommended architecture

sieve-based classifier

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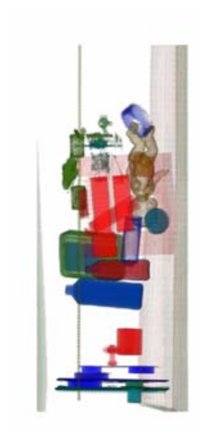
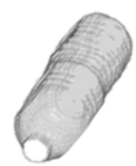


→ Classifier →



↑

Training data

•Classifier features derived from MEAN of all examples in the training set of 30 bags.

•Test every segment in channel-merged objects in BAG03, BAG06, BAG12 and BAG15.

•Scores are logarithmic distances between feature vector of unknown objects and target object.

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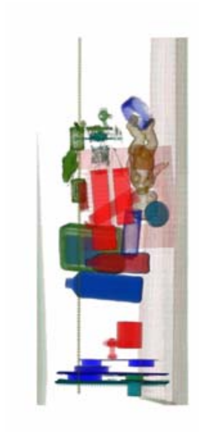
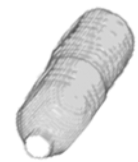
Recommended architecture
sieve-based classifier

University of East Anglia



Classifier



Training data

Target Object	Features used by classifier			Objects ranked by classifier score		
Water bottle	histogram	Mean density	Volume	Object	Bag	Score
	Yes	Yes	No	See above	**BAG15**	**0.1084**
				SS bottle	**BAG06**	**1.2236**
				SS bottle	**BAG06**	**1.6627**

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Sieve classifier results
Testing on training data

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Target Object	Features used by classifier			Objects ranked by classifier score	
	histogram	Mean density	Volume	Object	Score
Hard Drive	Yes	Yes	No	Hard Drive	0.011419
				Hard Drive	0.020486
				Hard Drive	0.028489
				laptop	0.061193
				Large Flashlight	0.06772
				Digital Camera	0.070232
				Hard Drive	0.084283

Target Object	Features used by classifier			Objects ranked by classifier score	
	histogram	Mean density	Volume	Object	Score
Water bottle 1	Yes	Yes	Yes	Water bottle 1	0.080262
				Water bottle 1	0.080262
				Liquid Lotion	0.3021
				Water bottle 2	0.54801
				Water bottle 3	0.55439
				Water bottle 3	0.74378
				Liquid Lotion	1.0428

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Questions

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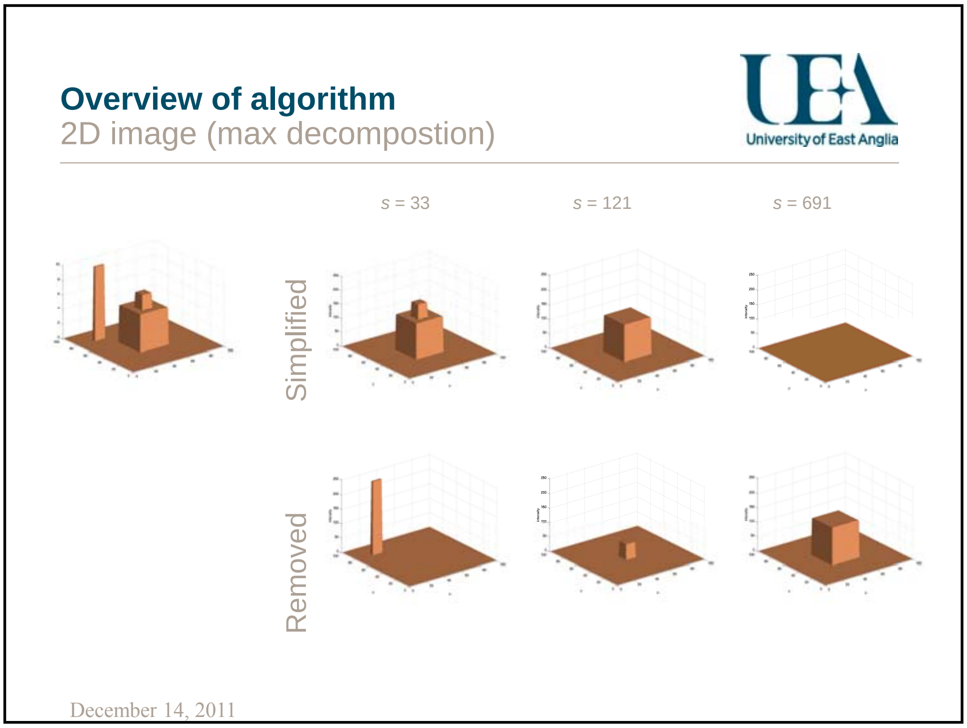
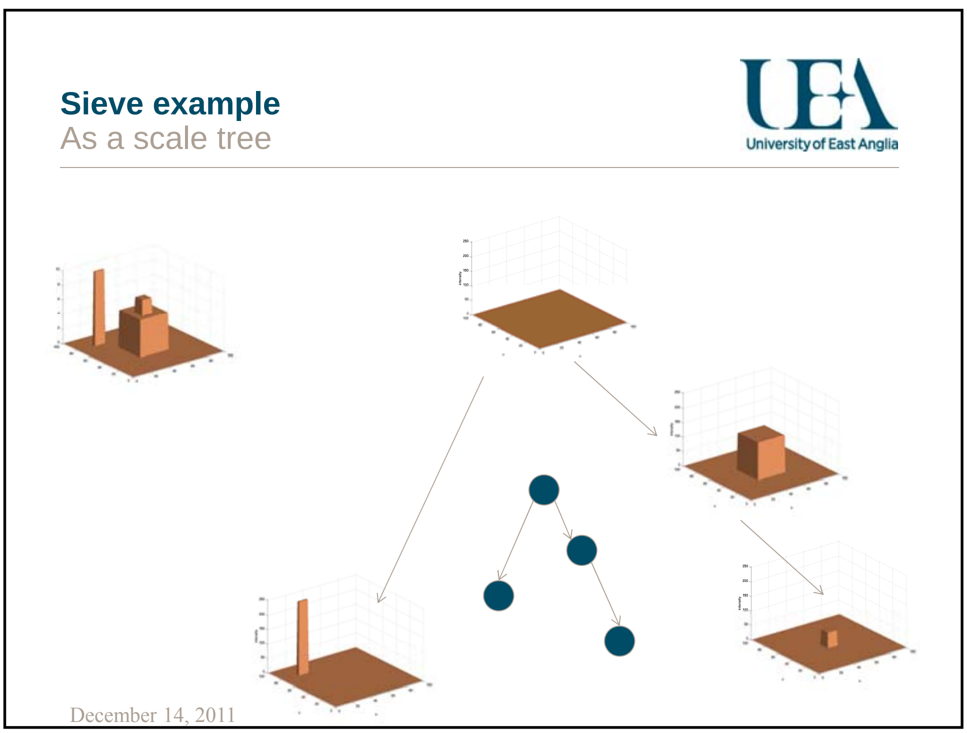
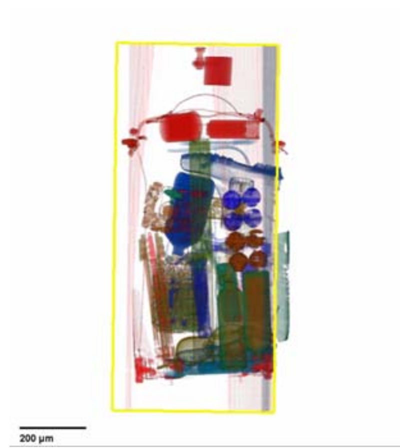

Overview of algorithm
2D image (max decompostion)
University of East Anglia
s = 33
s = 121
s = 691
Simplified
Removed
December 14, 2011


Sieve example
As a scale tree
University of East Anglia
December 14, 2011

Results comparison to AO Ground Truth

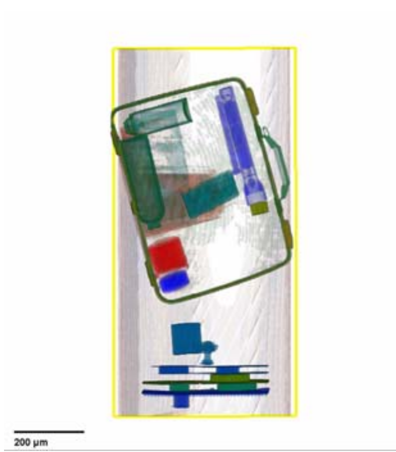
Bag 03



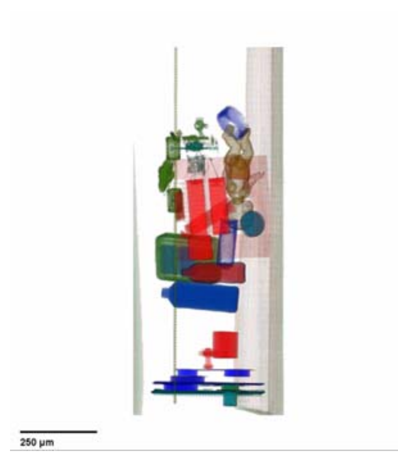
Bag 06

December 14, 2011

Results comparison to AO Ground Truth



Bag 12



Bag 15

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CT artifacts

Bag V12 Slice 538

Bag V12 Channel 3

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9.1.7 "ALERT Segmentation Initiative Presentation," Xin Feng, Taly Gilat-Schmidt, Wenjing Zhang, and Jun Zhang, Marquette University

ALERT Segmentation Initiative Presentation

Presented by
Dr. Xin Feng, Principal Investigator
Department of Electrical and Computer Engineering
Marquette University

December 8, 2011

1. Who are we and why are we here?

The segmentation research team:

- Marquette University
  - PI: Dr. Xin Feng, Electrical and Computer Engineering
  - Co-PI: Dr. Taly Gilat-Schmidt, Biomedical Engineering
  - RA: Wenjing Zhang, Ph.D. Candidate, EECE Department
- University of Wisconsin-Milwaukee
  - Co-PI: Dr. Jun Zhang, EECS Department
- Domain Expert/Mentor: Carl Crawford

2. Executive Summary

- What we developed:
  - a fully-automated, true 3D segmentation algorithm
- What we accomplished:

A three-stage merging-splitting strategy

- Stage One: split image into more homogeneous regions by gradient; generate seeds map
- Stage Two: grow each regions with adaptive thresholding
- Stage Three: merge fragmented objects; extract texture as new feature for clustering and merging
- New heuristic method to merge objects fragmented by metal streaks

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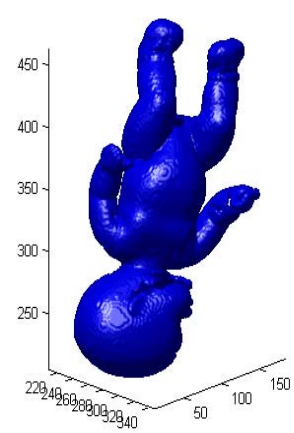
Sample Result

Properties	Value
No. of voxels	175,675
Mass-CT	270.51g
Volume	216.77cm^3
Density-CT	1.248g/cc



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Presentation Outline

1. The Research Team
2. Executive Summary
3. **Problem Statements/Challenges**
4. The Algorithm
5. Image Examples
6. Adaptive Splitting/Merging
7. Summary of Strengths and Weaknesses
8. Future Work

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3. Problem Statements and Challenges

- Problem Statement:
  - Given a set of CT-scanned luggage image files, deliver an automatic 3D segmentation algorithm to segment and label all objects with (HU>500) and (volume > $50mm^3$)
- Problem Challenges:
  - Homogenous and heterogeneous objects
  - Massive metal streaks all over
  - Potential threats with various shapes and density
  - Limited feature (intensity only)
- Algorithmic Challenges
  - No one-size-fit-all; needs integrated methods
  - Streak identification/removal without raw data: how?
  - Needs innovative methods for slitting/merging

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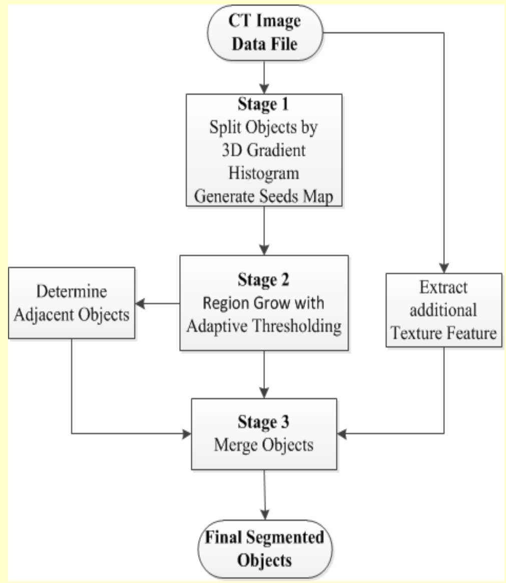
Presentation Outline

4. The Algorithm

- Three specific challenges
  - Splitting/Merging: always a "contradictory pair"
  - Region grow: how to determine the homogeneous area
  - Adding features: an effective way to improve overall accuracy

Algorithm Overview

- The three-stage strategy for splitting/merging/feature extraction
  - Stage one: splitting objects using gradient histogram; generating seeds map
  - Stage two: region growing by adaptive thresholding
  - Stage three:
    merge with extra features: (intensity, texture)
    Merge fragmented objects caused by streaks



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Algorithm Details

- **Splitting/Generating Seeds Map**
- **Adaptive Region Growing**
- **Merging**

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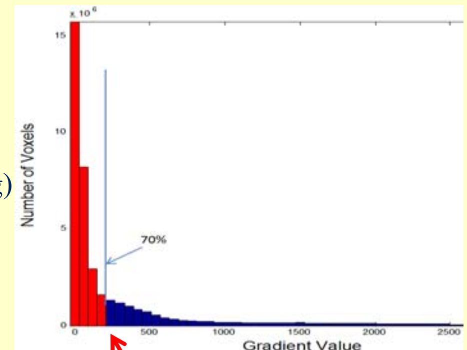
Stage 1: Splitting/Generating Seeds Map

- Splitting the 3D image into more homogenous sub-regions
- Homogeneity
  - Low gradient voxels
  - Each sub-region has near-uniform density
  - Will be used as seeds map for Stage Two (region growing)
- 3D Gradient of image

$$\nabla f = (G_x\, G_y\, G_z) = \left(\frac{\partial f}{\partial x}\ \frac{\partial f}{\partial y}\ \frac{\partial f}{\partial z}\right)$$

$$|\nabla f| = (G_x^2 + G_y^2 + G_z^2)^{1/2}$$

Gradient operator: Sobel

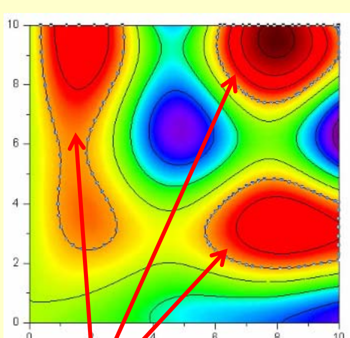


λ: cut-off threshold

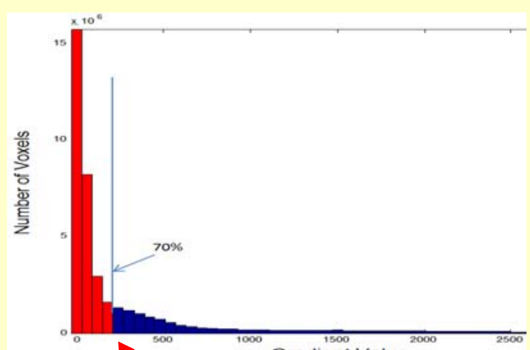
- Generating seeds map using low gradient voxels

Stage 1: Splitting/Generating Seeds Map

- Only homogenous regions are chosen as seeds map
- The cut-off threshold λ=70%



Selected Seeds Map

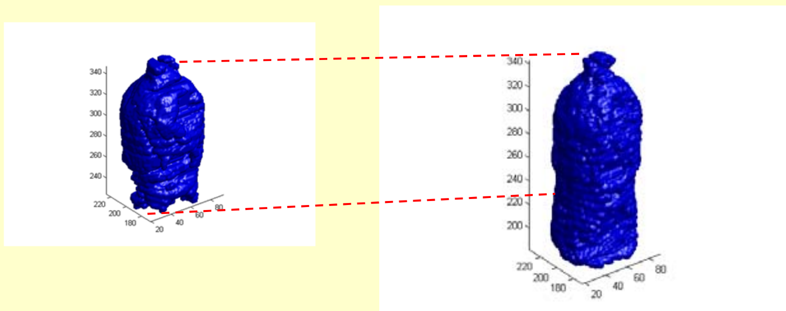


λ: cut-off threshold

Stage 1 Example

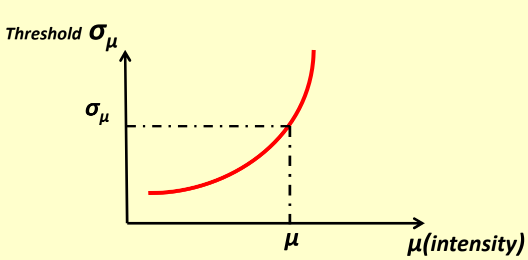
Intensity based CCL segmentation

Gradient based seeds map



Stage 2: Region Grow by Adaptive Thresholding

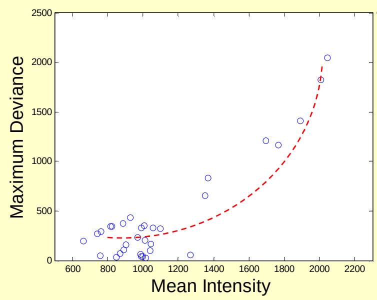
- Goal: fully grow the initial seeds map
- Challenges in region grow:
  - Intensity variation within objects
  - Fixed threshold will cause over/under segmentation
  - Percentage threshold σ_μ with respect to intensity is inappropriate (because of nonlinear variation of intensity levels)

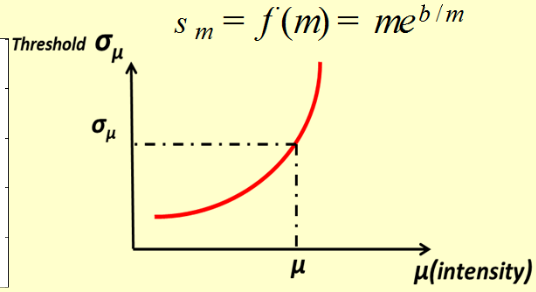


Stage 2: Region Grow by Adaptive Thresholding

- Study found the variation of intensities within the objects may be caused by scattering effects of the x-ray
- Proposed solution: model the region growing threshold σ_μ as nonlinear function of intensity level of the object:

$$s_m = f(m) = me^{b/m}$$





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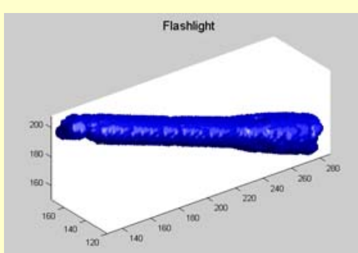
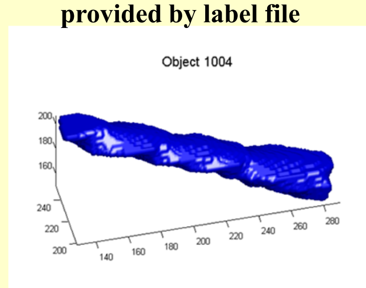
Stage 2 Example of Nonlinear Threshold

Segmented Region grow result with nonlinear threshold



Segmented image provided by label file



Properties	Values
No. of Voxels	38,259
Mass-CT	110.59g
Volume	47.21cm^3
Density-CT	2.34g/cc

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Stage 3: Merging Objects

- Challenges:
  - The single feature measure of intensity is inadequate for merging fragmented objects
  - Streak artifacts caused by high-density metal objects severely fragmented neighborhood objects

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Merging Fragmented Objects

- Proposed solution 1: Apply heuristic rules
  - Observation: fragmented object caused by streaks may still be weakly connected by a few voxels
  - Identify regions with adjacent edges
  - Caution: irrelevant objects may also share borders with other objects
- Proposed solution 2:
  - Extract texture as new feature by texture analysis
  - Consider mean texture and intensity as 2D feature
  - Perform the recursive clustering analysis to merge two closest objects according to:

$$D(object[i], object[j]) < d$$

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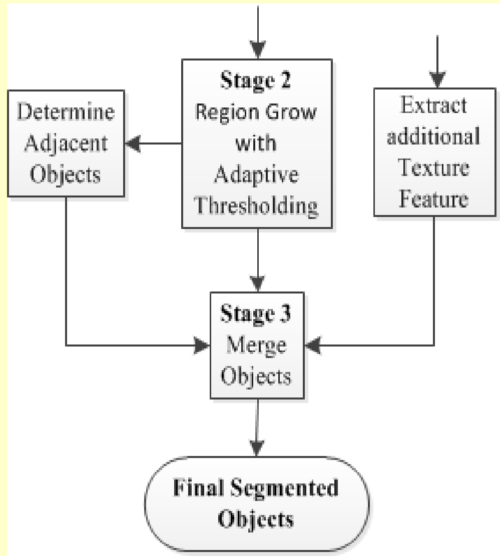
Stage 3: Merging Method

- Merging heuristic:
  - If
    two "separated" objects have small distance in feature space,
  - and
    they share adjacent edge with quite a few touching" voxels
  - Then
    they are considered as one object and should be merged



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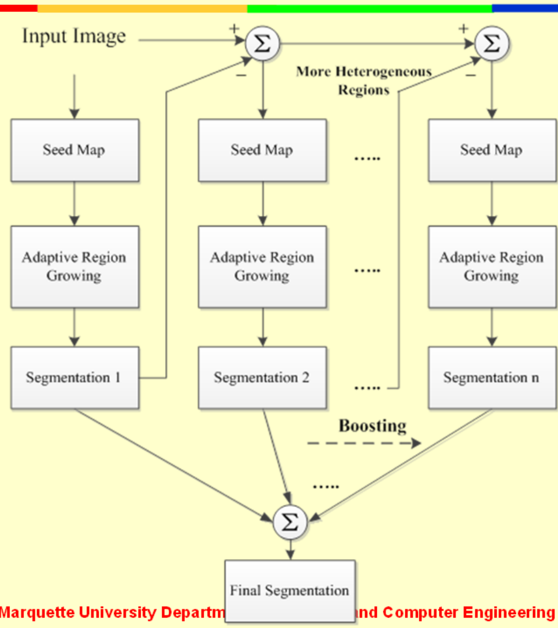
Recursive Implementation



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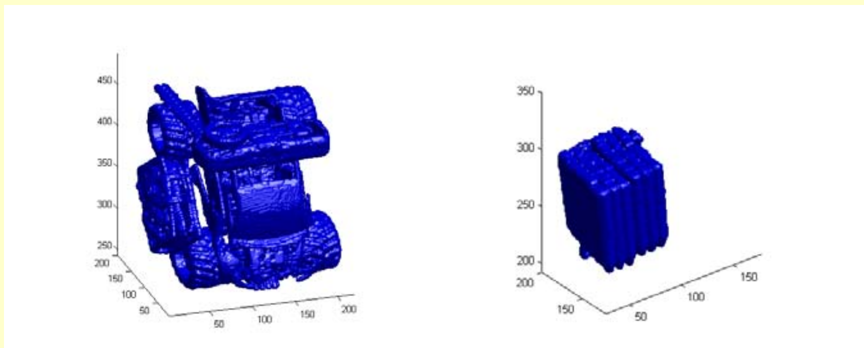
Segmentation of Heterogeneous Objects by Iteration



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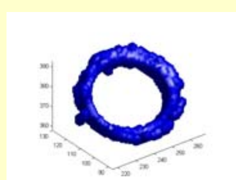
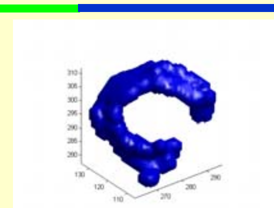
Example: from Stage 1 to Stage 2

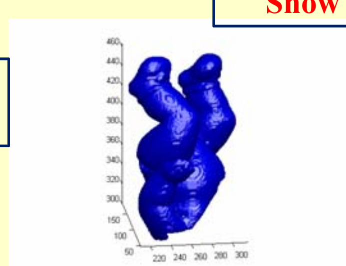
Stag One:
Splitting
and
Seeds map

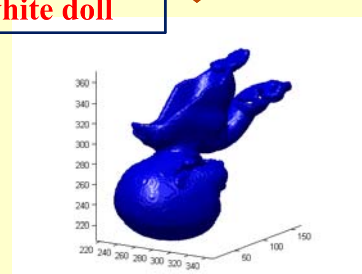




Object 3001
Snow white doll

Stage Two
Region grow





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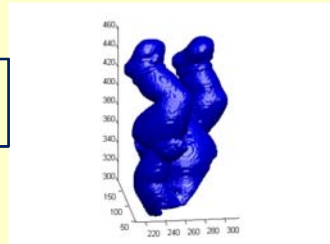
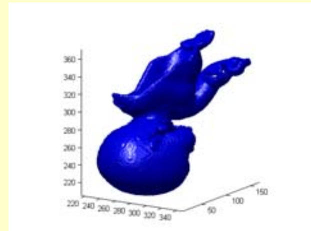
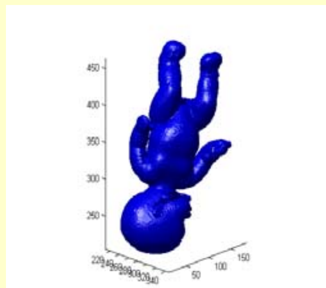
Example: from Stage 2 to Stage 3

Stage Two Region Grow





Stage Three Merging



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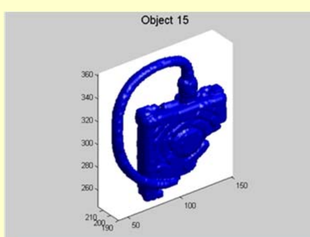
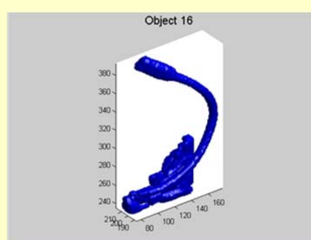
More Merging Examples

- Problem : single object is fragmented by metal streaks





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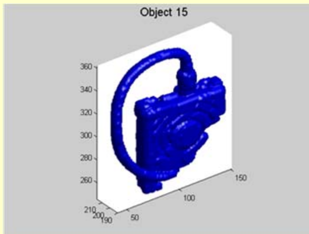
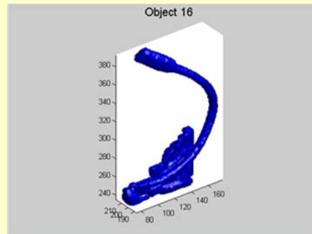
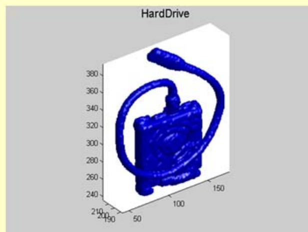
More Merging Examples







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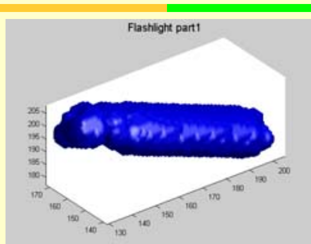
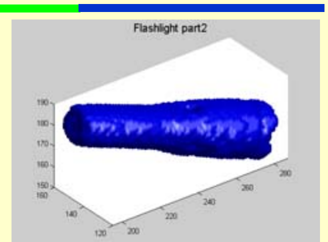
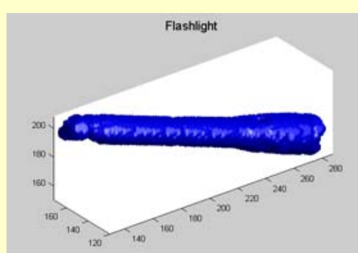
More Merging Examples







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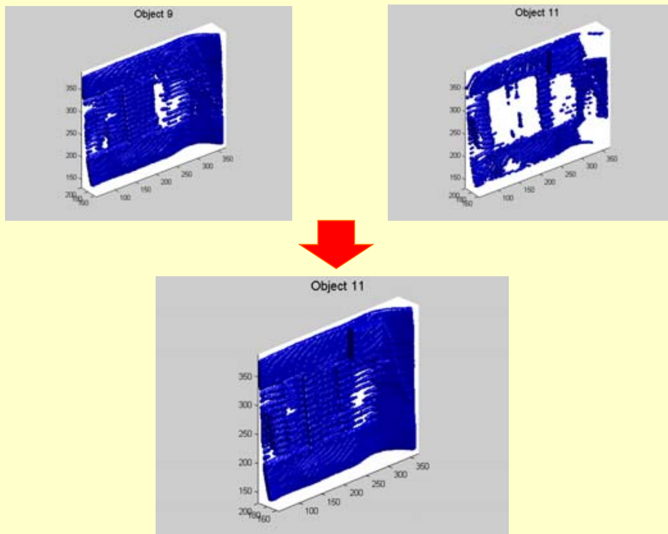
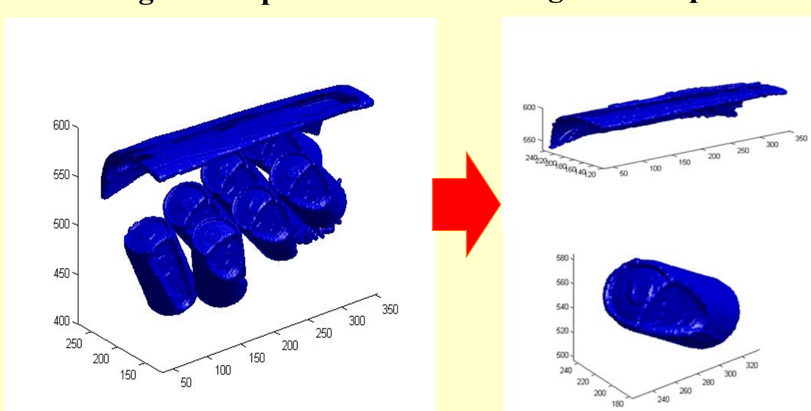
More Merging Examples



Performance Comparison with Standard CCL

Split a robber sheet from the group of cans

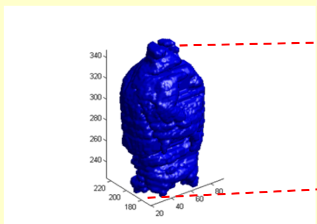
Existing CCL: split failed | **New algorithm: split succeeded**

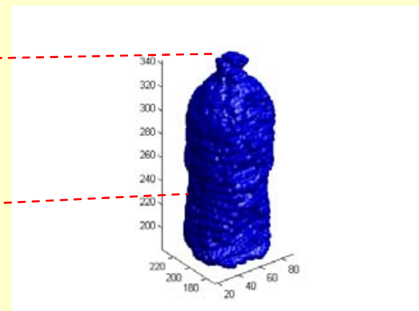


Performance Comparison with Standard CCL

Existing CCL:
Unable to merge fragmented object caused by streak artifacts

New Algorithm:
Successfully merged fragmented objects





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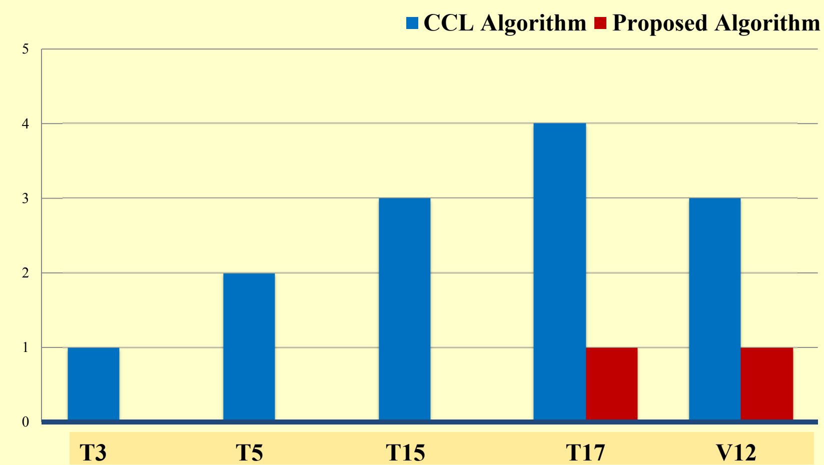
Performance Comparison with Standard CCL

Number of False Split Objects



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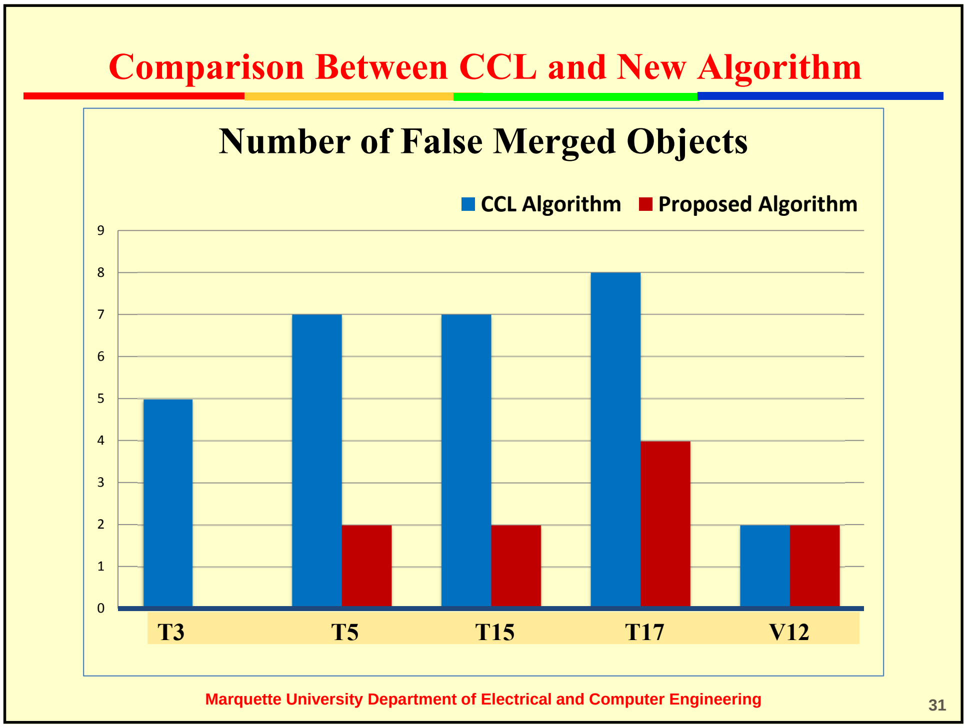
Comparison Between CCL and New Algorithm
Number of False Merged Objects
CCL Algorithm
Proposed Algorithm
0
1
2
3
4
5
6
7
8
9
T3
T5
T15
T17
V12
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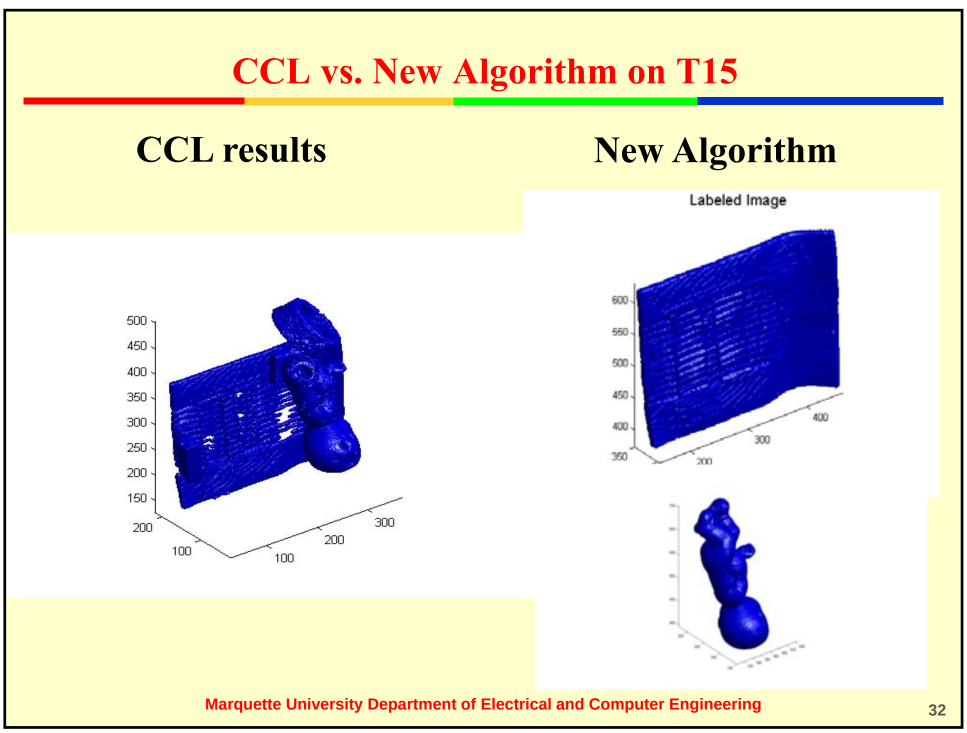
CCL vs. New Algorithm on T15
CCL results
New Algorithm
Labeled Image
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Summary of Strengths and Weaknesses

- Strengths:
  - A three-stage splitting-segmentation-merging approach
  - Unique heuristic merging of fragmented object caused by streaks
  - Added feature for better merging results
  - Completely automatic,; Robust performance
- Weakness:
  - Streak removal: "work-around it" instead of "removing it" due to lacking of raw CT data (sinogram data)
  - Physical measurement results in 15% less then actual, probably due to "dark" streaks
  - Tuning of two parameters (λ and σ_{μ}) affects splitting and merging results, needs fine tuning

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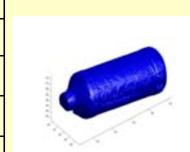
Comparison of Physical Features

Item Number	Calculated from Label	Segmented Results	Errors	Ground Truth
2002	Water Bottle			
No. of voxels	405,510	355,824	-12%	
Volume(ml)	502.39	440.84	-12%	500
Mass(g)	477.59	449.69	-5.8%	510
Density(g/cc^3)	0.95	1.02	+2%	1.00
4003	Robbing Alcohol Bottle			
No. of voxels	916,592	826,379	-9.8%	N/A
Volume(ml)	1135.58	1023.81	-9.8%	N/A
Mass(g)	953.90	919.51	-3.6%	N/A
Density(g/cc^3)	0.84	0.89	+5.6%	N/A



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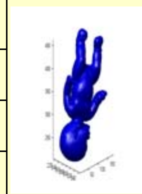
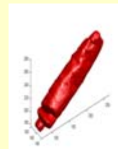
Comparison of Physical Features

Item Number	Calculated from Label	Segmented Results	Differences	Ground Truth
3001	Snow White Doll			
No. of voxels	210,063	175,675	-16.1%	N/A
Volume(ml)	260.25	270.51	+3.0%	N/A
Mass(g)	166.71	216.77	+23.0%	N/A
Density(g/cc^3)	0.64	1.25	+48.8%	N/A
3	Toothpaste			
No. of voxels	158,260	114,974	-27.3%	N/A
Volume(ml)	196.07	142.44	-27.3%	N/A
Mass(g)	279.75	208.02	-25.6%	N/A
Density(g/cc^3)	1.43	1.46	+2.1%	N/A





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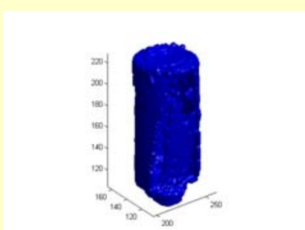
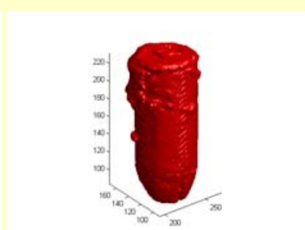
Comparisons of “ground truth”

Segmented image

Label image

Object 70:
OFF repellent





Volume (ml)	158.63	346.49
Mass(g)	136.47	307.98
Density(g/cc^3)	0.86	0.88

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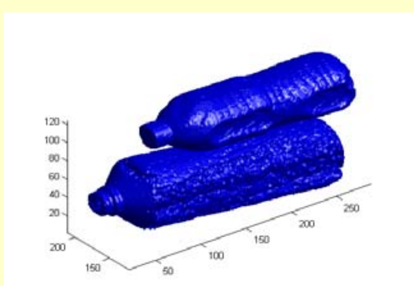
Risks and Mitigation

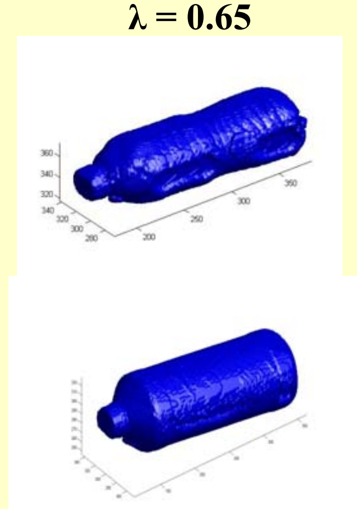
- Risk: tuning of two parameters (λ and σ_μ) affects splitting/merging results
  - Always a pair of "contradictive actions"
  - Cutoff parameter $\boldsymbol{\lambda}$ of the gradient histogram is critical in selecting homogeneous areas thus affects splitting
  - Adaptive threshold $\boldsymbol{\sigma_\mu}$ needs to be fine tuned, affecting merging.
- Mitigation:
  - Split more aggressively with lower $\boldsymbol{\lambda}$ in the gradient histogram
  - Grow more generously with higher threshold $\boldsymbol{\sigma_\mu}$

Parameter Tuning: λ (gradient cut-off threshold)

λ= 0.70

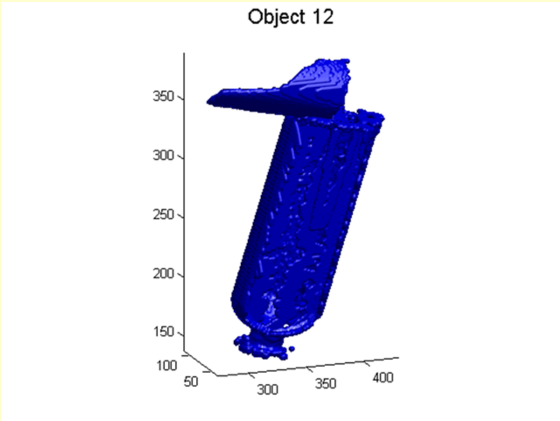


λ = 0.65



Examples Our Algorithm Did Not Work Well

Bad example from V12



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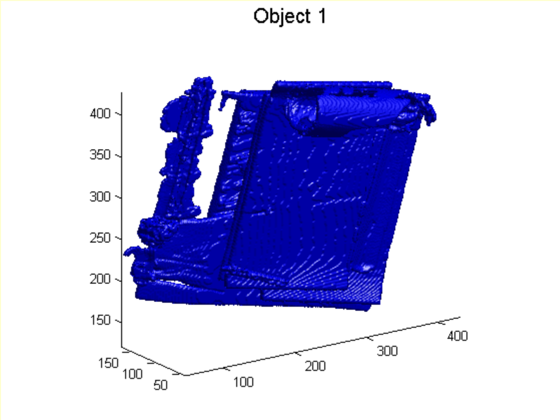
Examples Our Algorithm Did Not Work Well

Bad example from V12



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Presentation Outline

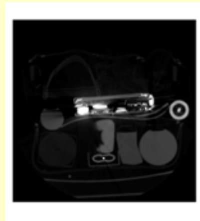
1. The Research Team
2. Executive Summary
3. Problem Statements/Challenges
4. The Algorithm
5. Image Examples
6. Splitting/Merging
7. Summary of Strengths and Weaknesses
8. **Future Work**

Future Work (1): Evaluation and Detection

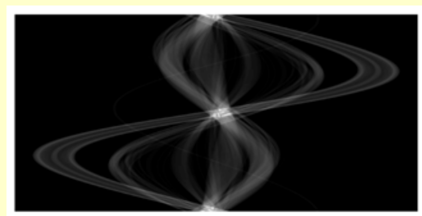
- Establish the evaluation criteria
- Establish the evaluation method
- Intelligent Detection

Future Work (2): Metal Streak Identification

1. Segment metal in image volume based on HU number




2. Forward project metal image to create metal sinogram



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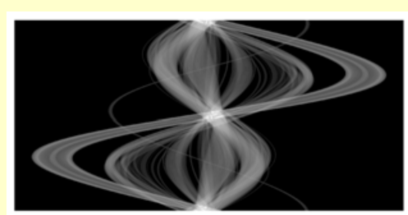
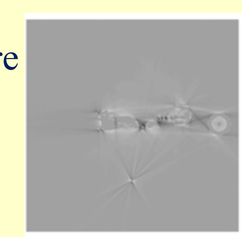
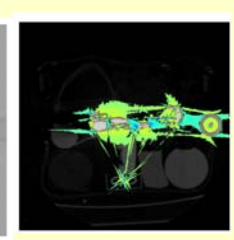
Future Work (2): Metal Streak Identification

3. Simulate beam hardening by taking square root of metal sinogram



4. Create streak image by thresholding image reconstructed from square root sinogram

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References

- Luis Ugarriza et al. , "Automatic Image Segmentation by Dynamic Region Growth and Multiresolution Merging", *IEEE TRANSACTIONS ON IMAGE PROCESSING*, Vol. 18, No. 10, Oct. 2009.
- Z. Ying; et al, "Method of and system for 3D display of multi-energy computed tomography images," U.S. Patent 20,060,274,066, December 7, 2006
- S. Simanovsky, Z. Ying, and C. R. Crawford, "Method of and system for splitting compound objects in multi-energy computed tomography images," U.S. Patent 7,539,337, May 26, 2009.
- Final Report, *2nd Algorithm Development for Security Applications Workshop (ADSA02)*, ALERT Center of Excellence, Northeastern University, October 2009.
- M. Petrou and C. Petrou, *Image Processing: The Fundamentals, 2nd ed.*, Wiley, New York, 2010.
- Z. Lin, J. Jin, and H. Talbot, "Unseeded region growing for 3D image segmentation," Proceedings, Visualisation 2000, December, 2000.

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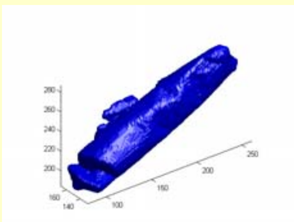
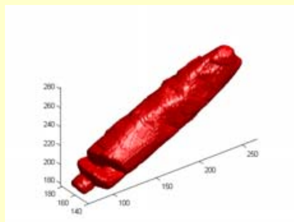
THANK YOU!

xin.feng@mu.edu

Examples of Results

Segmented image | **Label image** | **Object 3: toothpaste**





Volume	196.07	142.44
Mass	279.75	208.02
Density	1.43	1.46

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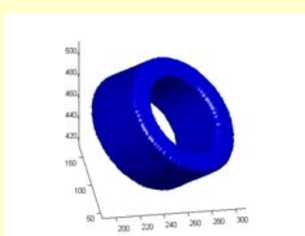
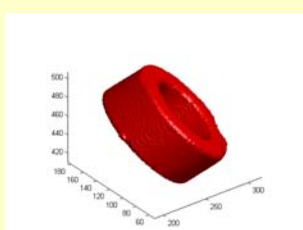
Examples of Results

Segmented image | **Label image** | **Object 59: duct tape**





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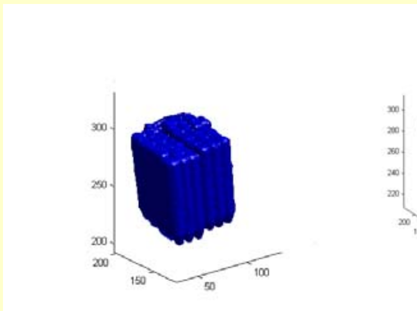
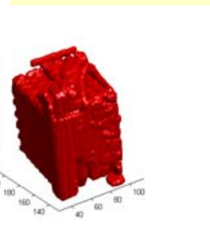
Examples of Results

Segmented image | **Label image** | **Object 60: Crayons**



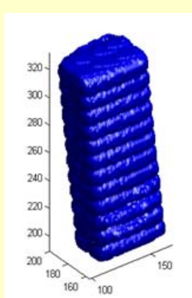


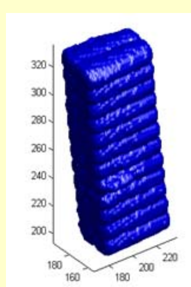
Examples of Results

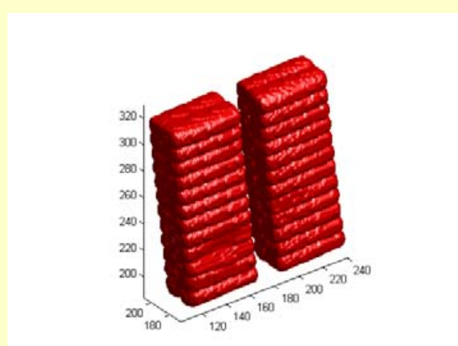
Segmented image

Label image

Object 3005: battery pack

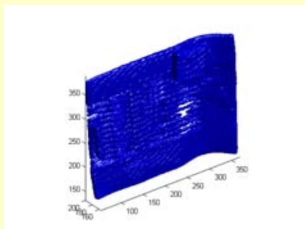


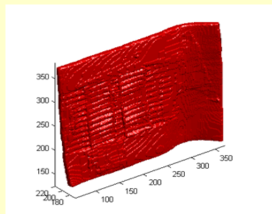




Examples of Results

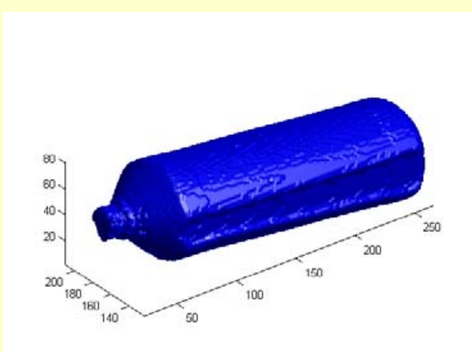
Segmented image | **Label image** | **Object 8028: Neoprene (thick)**

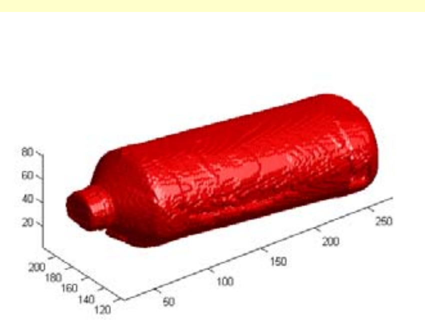




Comparison with Label Object 4003

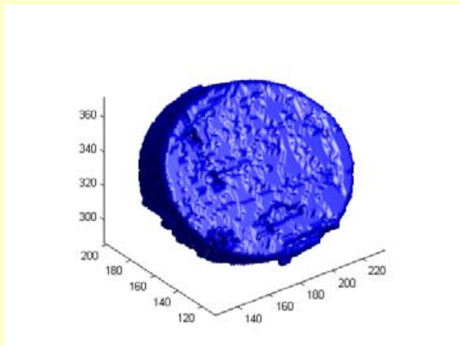
The New Algorithm | **Label Results**



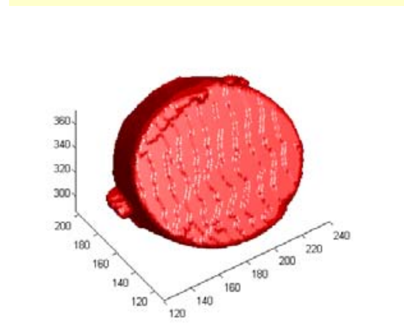


Comparison with Label Object 8018

The New Algorithm



Label Result



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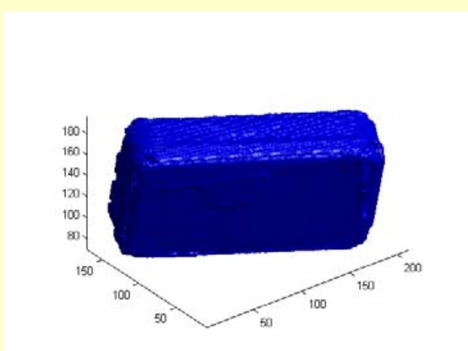
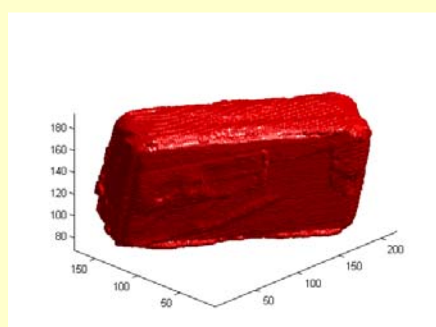
Comparison with Label Object 9995

Proposed Algorithm



Label Result



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9.1.8 "Security Screening Segmentation Challenge," Leo Grady, Timo Kohlberger, Vivek Singh, Claus Bahlmann and Dorin Comaniciu, Siemens Corporate Research

Security Screening Segmentation Challenge

Leo Grady, Timo Kohlberger, Vivek Singh, Claus Bahlmann, Dorin Comaniciu

Image Analytics and Informatics
Siemens Corporate Research, Princeton NJ

SIEMENS

SIEMENS CORPORATE RESEARCH

Executive Summary

System	Siemens Technology	Successes	Challenges
1) Metal artifact reduction 2) Bag isolation 3) Segmentation 4) Automated confidence measure	1) Fast Markov Random Field optimization 2) Recursive Isoperimetric Algorithm 3) Statistical learning of segmentation confidence measure	1) Artifact reduction able to mitigate effects of metal 2) Able to separate touching objects 3) Able to group large numbers of small above-threshold objects 4) Provide an accurate confidence level of segmentation quality	1) Not capturing object parts below 500MHUs 2) Not separating objects with a relatively large area surface contact 3) More data/testing needed 4) Not taking advantage of semantic content to guide segmentation

2

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Siemens Corporate Research


Princeton, USA

- Experts in medical imaging software and algorithms
- ~100 PhD-level people working on medical imaging
- Basic research ←→ clinical products

Internationally recognized team

MICCAI

Winner of segmentation challenge in 2009 and 2011

Winner of young scientist award for 2011, 2010, 2007 - runner-up 2008

CVPR
June 13-18, 2010
San Francisco, CA

Winner of 2010 Longuet-Higgens Prize for fundamental contributions in Computer Vision

3

SIEMENS

SIEMENS CORPORATE RESEARCH

Researchers

Dr. Leo Grady

- Principal Research Scientist
- PhD from Boston University in 2003
- Expertise: Image segmentation , graph theory, optimization
- ~50 papers, ~1,200 total citations, h-index: 16,
- 26 granted patents, ~40 additional patents pending.
- Software for 15 Siemens products and 4 products for Siemens partners
- New book: Discrete Calculus, 2010 Springer

Dr. Timo Kohlberger

- Research Scientist
- PhD from University of Mannheim, 2005
- Expertise: Model-based segmentation, parallel computing
- Best paper award by the Pattern Recognition Society in 2003

Dr. Vivek Singh

- Research Scientist
- PhD from University of Southern California in 2011
- Expertise: Computer vision, machine learning
- Best paper at SMiCV

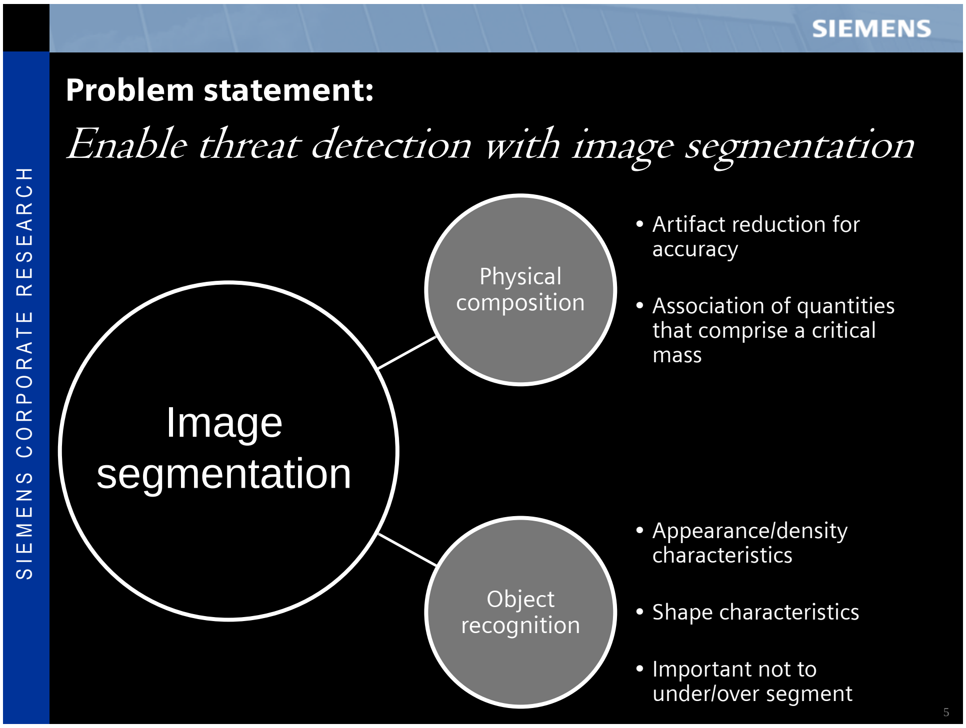
Dr. Claus Bahlmann

- Project manager
- PhD from University of Freiburg in 2004
- Focus on projects in safety, security, mobility, energy, and healthcare
- Expertise: Pattern recognition, computer vision, machine learning
- Best paper award in 2002 IWFHR
- PhD thesis won Wolfgang-Gentner-Nachwuchsförderpreis award

Dr. Dorin Comaniciu

- Global Technology Leader for Image Analytics and Informatics
- PhD from Rutgers University in 1999
- Expertise: Machine learning, informatics
- 200 papers, 12,000 citations, h-index: 35
- 82 patents
- Won best paper award at CVPR and MICCAI. Won Top Inventor award at Siemens. Won Longuet-Higgins award for fundamental contributions to computer vision

4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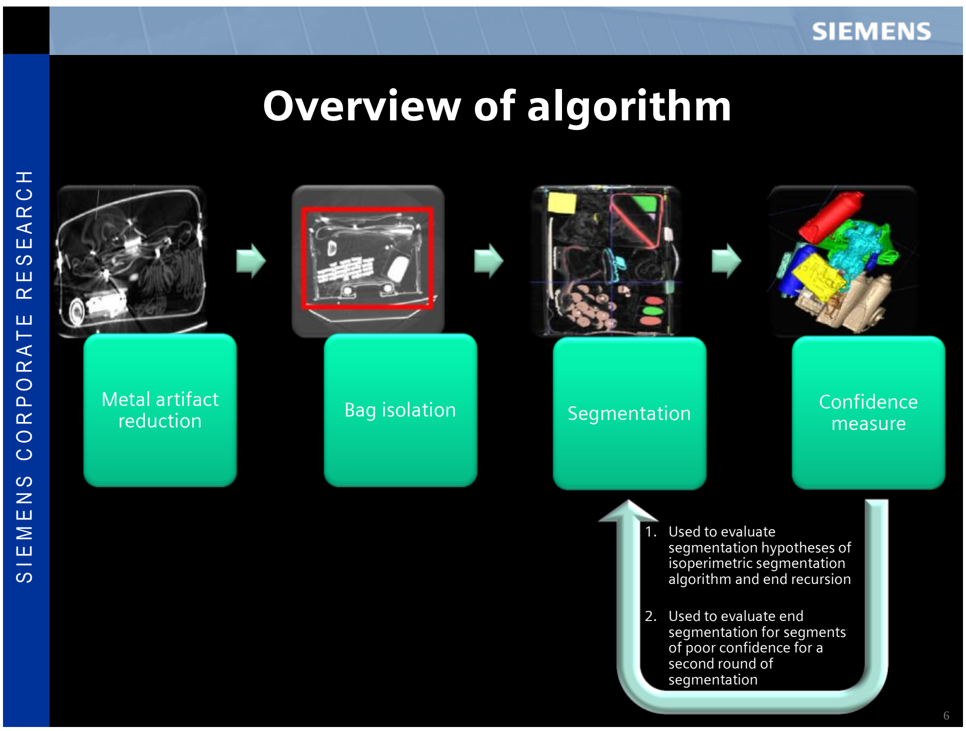
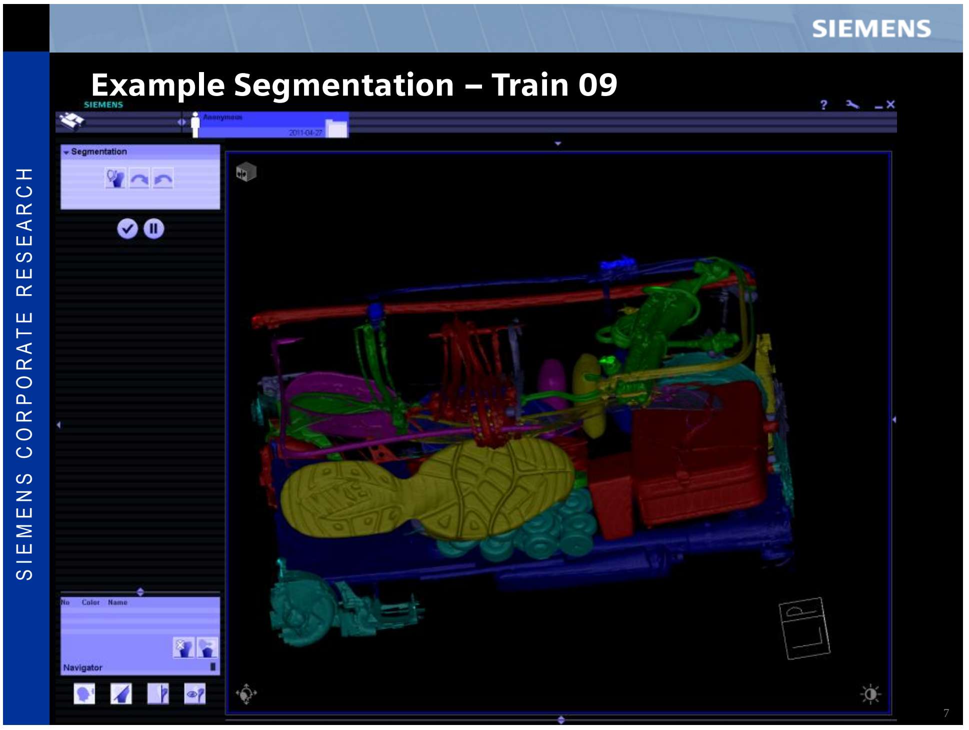
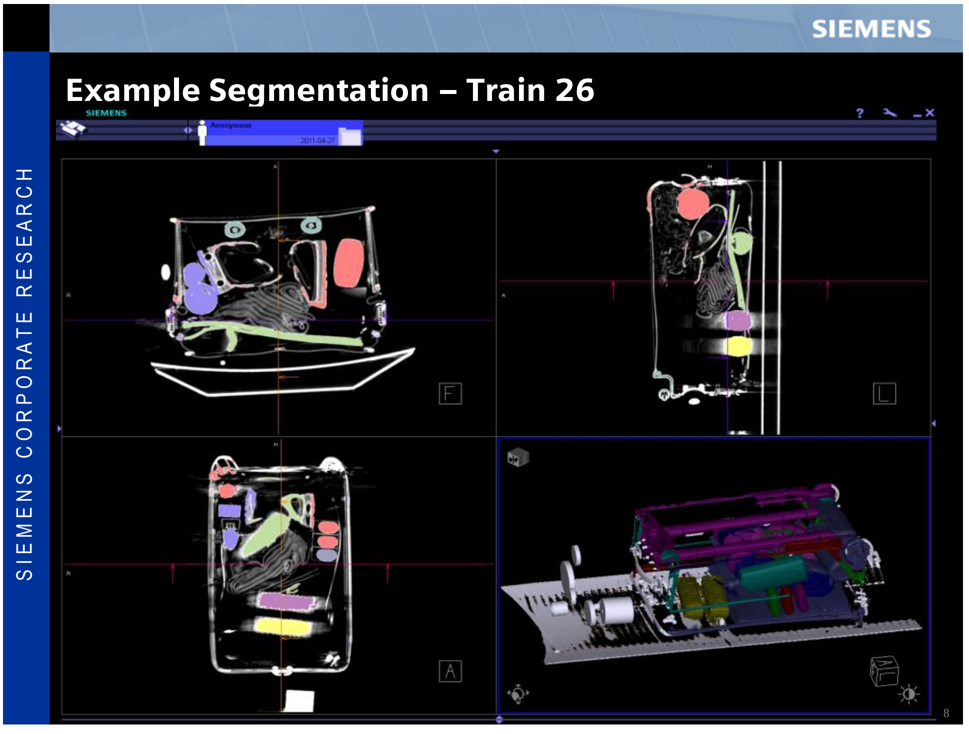
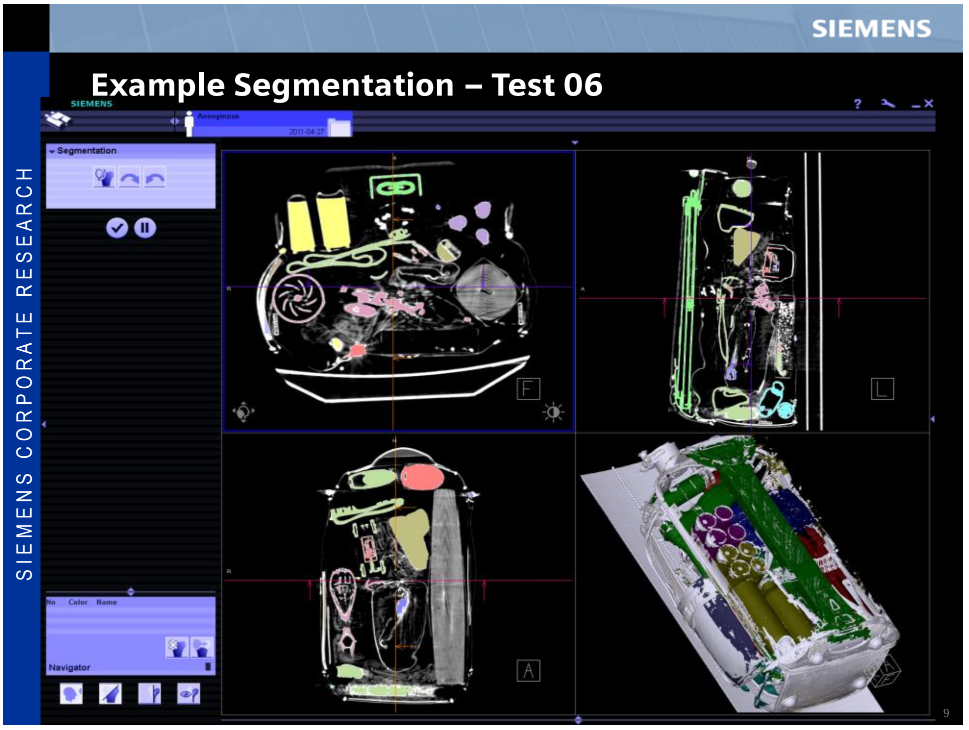
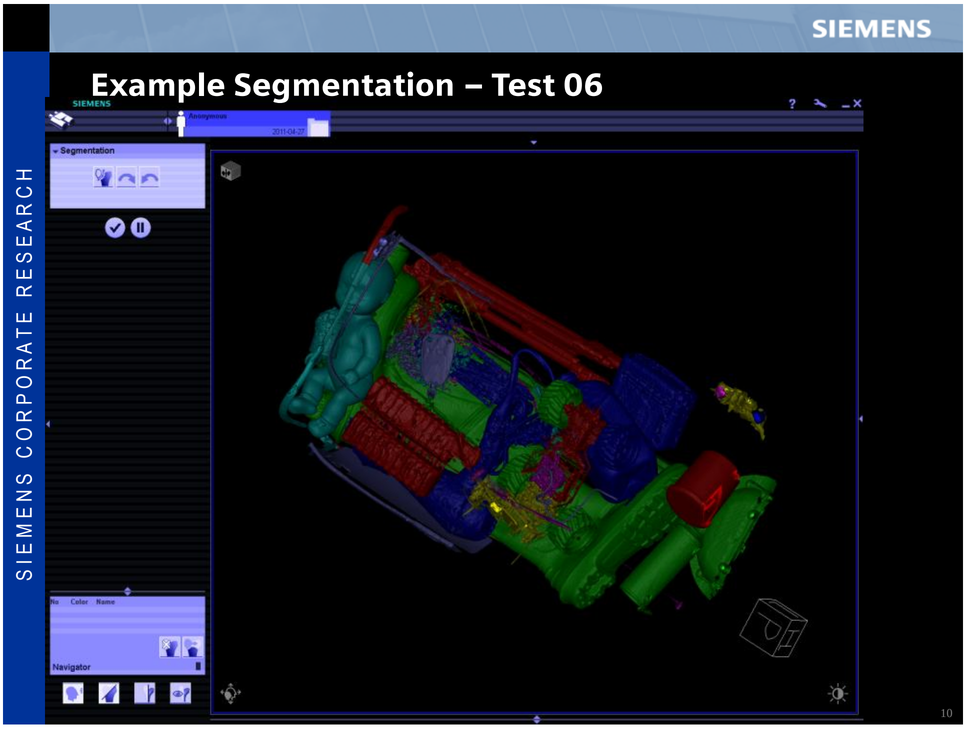
SIEMENS CORPORATE RESEARCH
Problem statement:
Enable threat detection with image segmentation
Image segmentation
Physical composition
Object recognition
• Artifact reduction for accuracy
• Association of quantities that comprise a critical mass
• Appearance/density characteristics
• Shape characteristics
• Important not to under/over segment
5

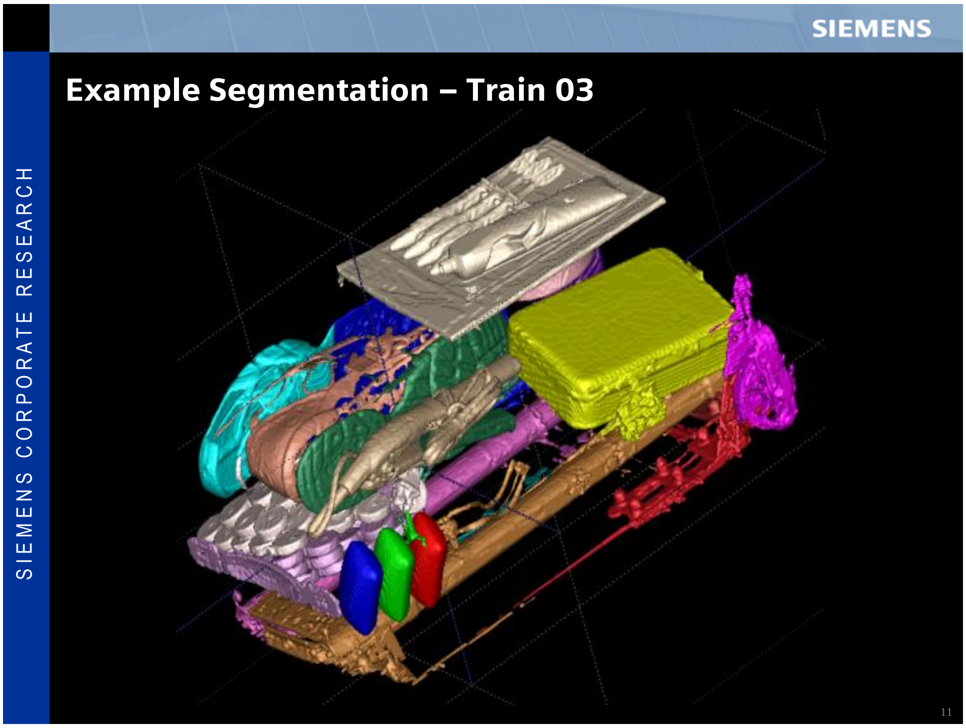

SIEMENS
SIEMENS CORPORATE RESEARCH
Overview of algorithm
Metal artifact reduction
Bag isolation
Segmentation
Confidence measure
1. Used to evaluate segmentation hypotheses of isoperimetric segmentation algorithm and end recursion
2. Used to evaluate end segmentation for segments of poor confidence for a second round of segmentation
6

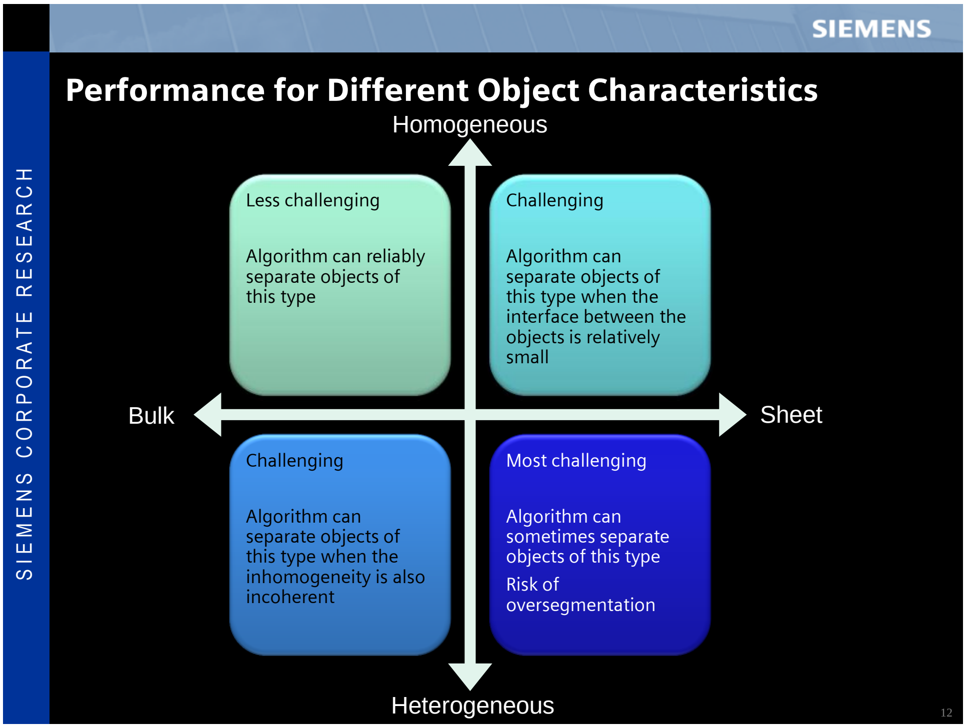

SIEMENS
Example Segmentation – Train 09
SIEMENS CORPORATE RESEARCH
Segmentation
Navigator
7


SIEMENS
Example Segmentation – Train 26
SIEMENS CORPORATE RESEARCH
F
L
A
8


SIEMENS
Example Segmentation – Test 06
SIEMENS CORPORATE RESEARCH
Segmentation
Navigator
9


SIEMENS
Example Segmentation – Test 06
SIEMENS CORPORATE RESEARCH
Segmentation
Navigator
10


SIEMENS
SIEMENS CORPORATE RESEARCH
Example Segmentation – Train 03
11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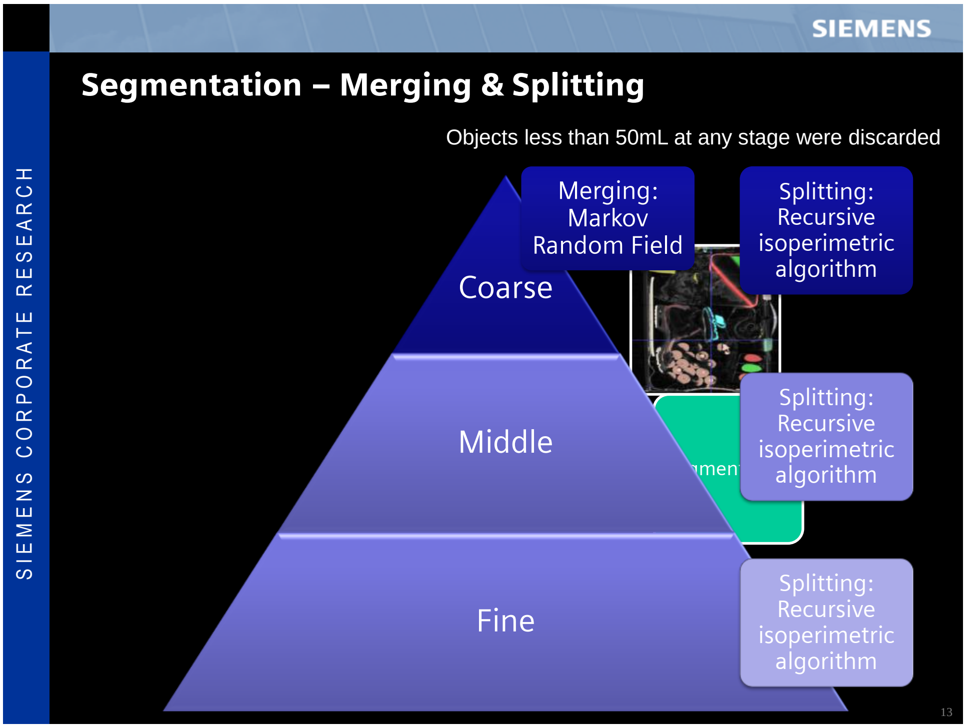
Performance for Different Object Characteristics
Homogeneous
Less challenging
Algorithm can reliably separate objects of this type
Challenging
Algorithm can separate objects of this type when the interface between the objects is relatively small
Bulk
Sheet
Challenging
Algorithm can separate objects of this type when the inhomogeneity is also incoherent
Most challenging
Algorithm can sometimes separate objects of this type
Risk of oversegmentation
Heterogeneous
12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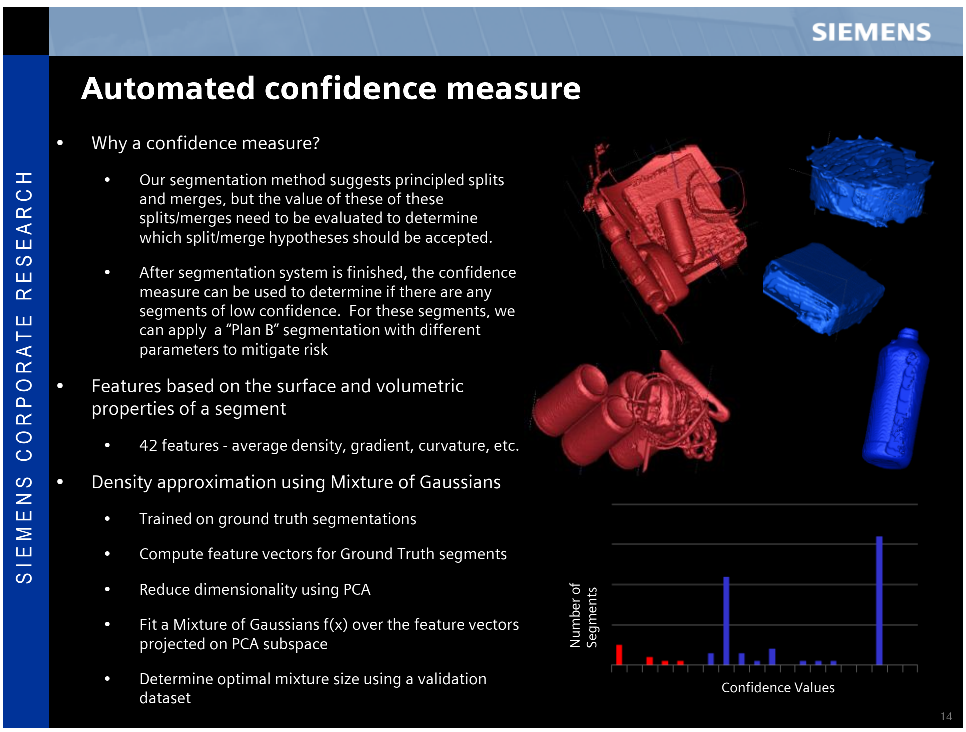
Segmentation – Merging & Splitting
Objects less than 50mL at any stage were discarded
Merging: Markov Random Field
Splitting: Recursive isoperimetric algorithm
Coarse
Middle
Splitting: Recursive isoperimetric algorithm
Fine
Splitting: Recursive isoperimetric algorithm
13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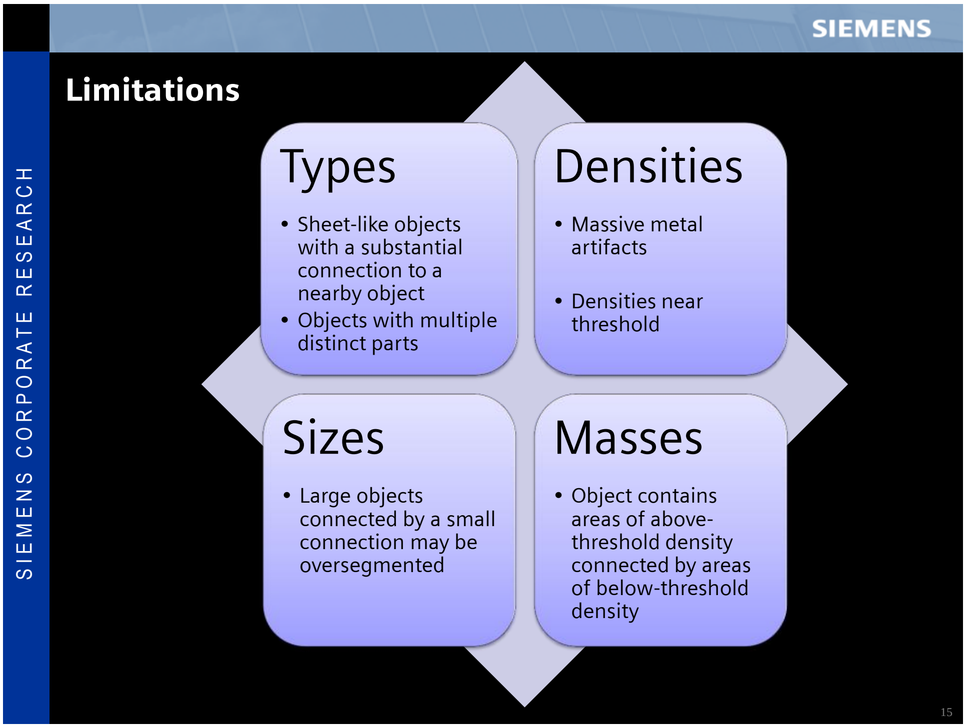
Automated confidence measure
• Why a confidence measure?
• Our segmentation method suggests principled splits and merges, but the value of these of these splits/merges need to be evaluated to determine which split/merge hypotheses should be accepted.
• After segmentation system is finished, the confidence measure can be used to determine if there are any segments of low confidence. For these segments, we can apply a "Plan B" segmentation with different parameters to mitigate risk
• Features based on the surface and volumetric properties of a segment
• 42 features - average density, gradient, curvature, etc.
• Density approximation using Mixture of Gaussians
• Trained on ground truth segmentations
• Compute feature vectors for Ground Truth segments
• Reduce dimensionality using PCA
• Fit a Mixture of Gaussians f(x) over the feature vectors projected on PCA subspace
• Determine optimal mixture size using a validation dataset
Number of Segments
Confidence Values
14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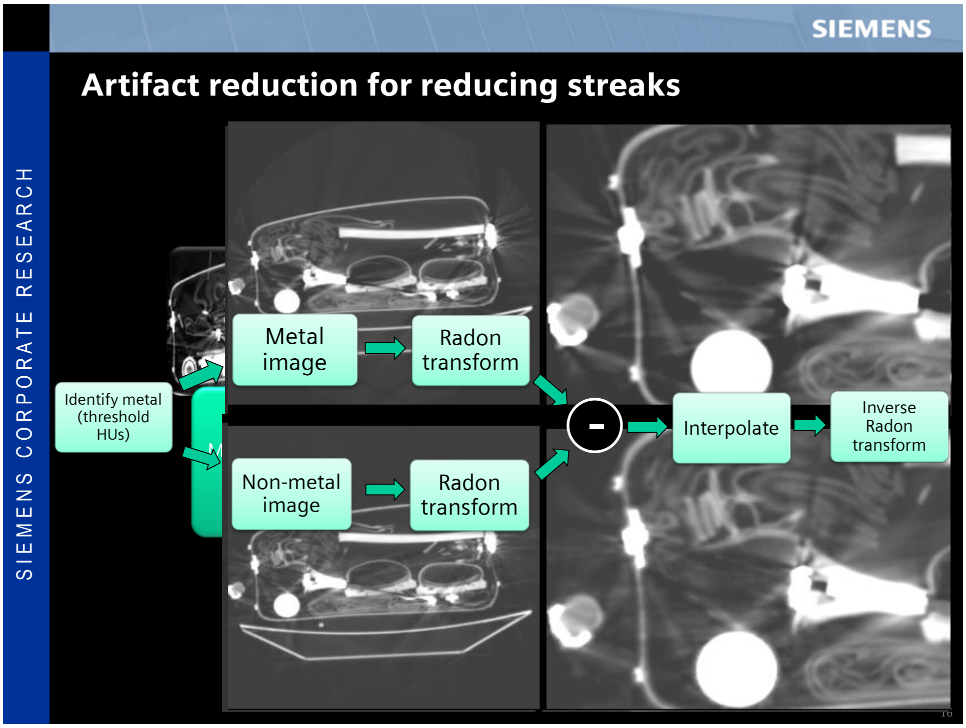
Limitations
Types
• Sheet-like objects with a substantial connection to a nearby object
• Objects with multiple distinct parts
Densities
• Massive metal artifacts
• Densities near threshold
Sizes
• Large objects connected by a small connection may be oversegmented
Masses
• Object contains areas of above-threshold density connected by areas of below-threshold density
15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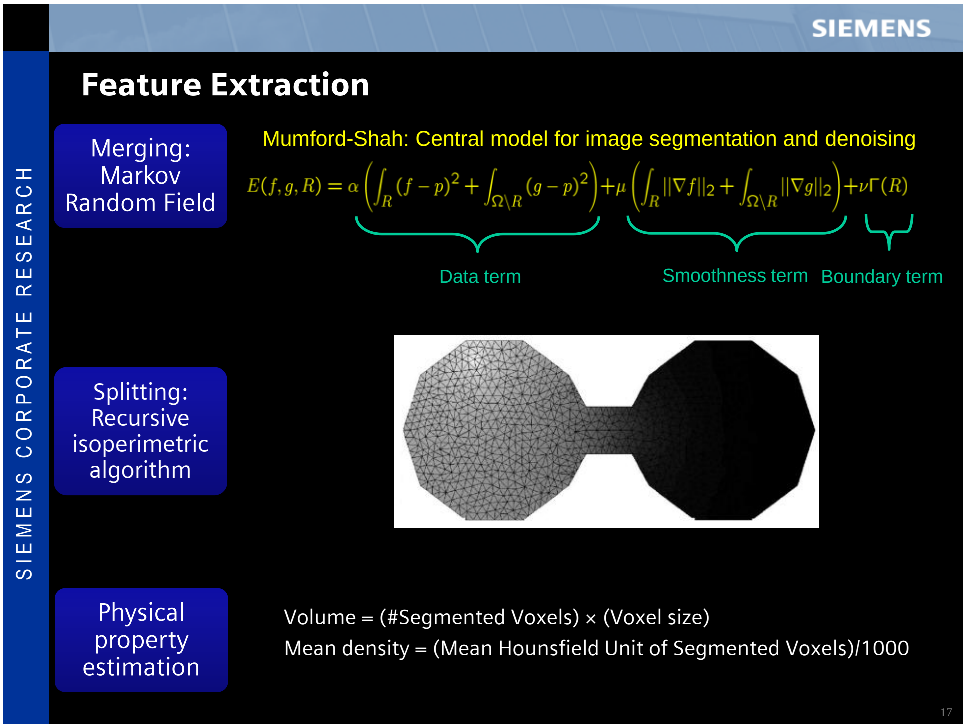
Artifact reduction for reducing streaks
Identify metal (threshold HUs)
Metal image
Radon transform
Non-metal image
Radon transform
-
Interpolate
Inverse Radon transform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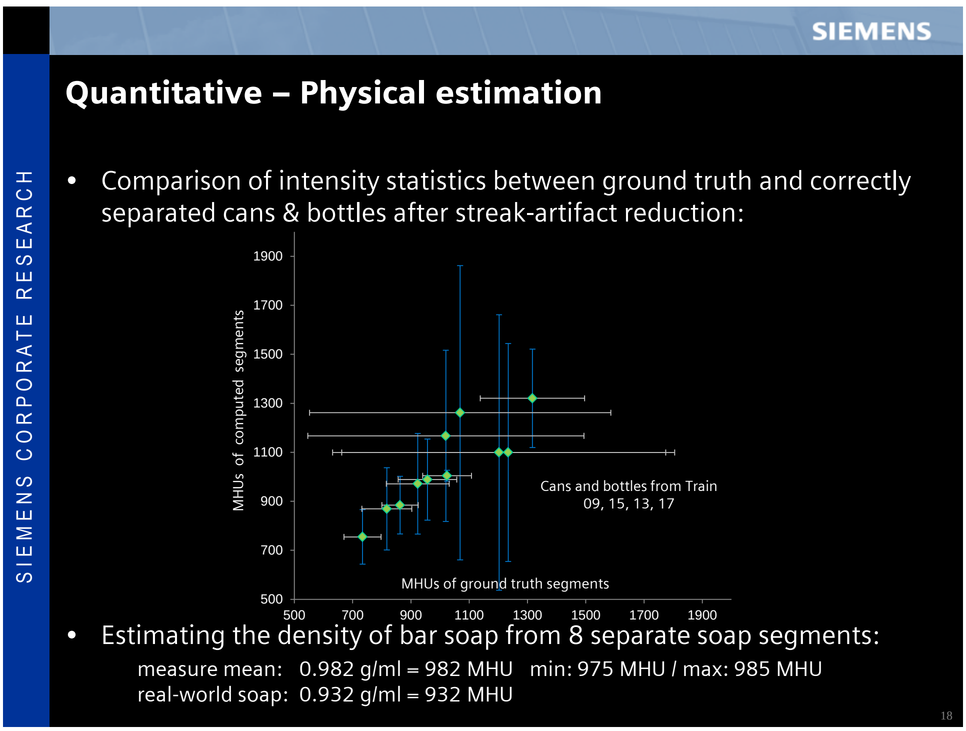
Feature Extraction
Merging: Markov Random Field
Mumford-Shah: Central model for image segmentation and denoising
$E(f,g,R) = \alpha\left(\int_R (f-p)^2 + \int_{\Omega\setminus R}(g-p)^2\right) + \mu\left(\int_R \|\nabla f\|_2 + \int_{\Omega\setminus R}\|\nabla g\|_2\right) + \nu\Gamma(R)$
Data term
Smoothness term
Boundary term
Splitting: Recursive isoperimetric algorithm
Physical property estimation
Volume = (#Segmented Voxels) × (Voxel size)
Mean density = (Mean Hounsfield Unit of Segmented Voxels)/1000
17


SIEMENS
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Quantitative – Physical estimation
• Comparison of intensity statistics between ground truth and correctly separated cans & bottles after streak-artifact reduction:
MHUs of computed segments
1900
1700
1500
1300
1100
900
700
500
Cans and bottles from Train 09, 15, 13, 17
MHUs of ground truth segments
500 700 900 1100 1300 1500 1700 1900
• Estimating the density of bar soap from 8 separate soap segments:
measure mean: 0.982 g/ml = 982 MHU min: 975 MHU / max: 985 MHU
real-world soap: 0.932 g/ml = 932 MHU
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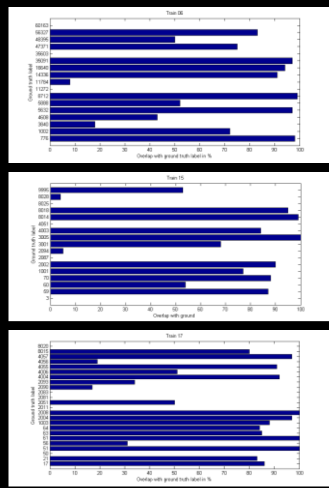
Quantitative - Overlap



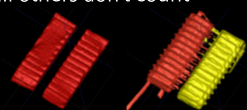
- Segmentation labels are matched to ground truth labels in order to maximize the relative overlap between segments
- Over-segmented labels are assigned to one ground truth label, intersections with other ground truth labels don't count

Boots, bag and flashlight in Train06:

ground truth segmentation

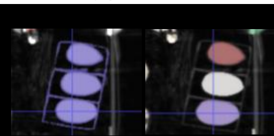
- In case of over-splits, only one sub-segment is assigned to a ground truth segment, all others don't count

Pack of batteries in Train06:



ground truth segmentation

Pack of soaps in Train03:



ground truth segmentation

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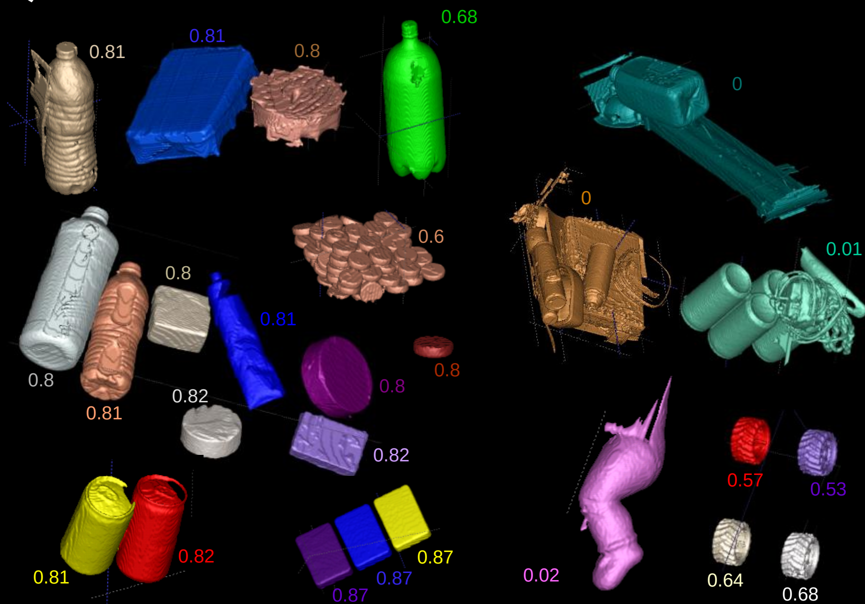
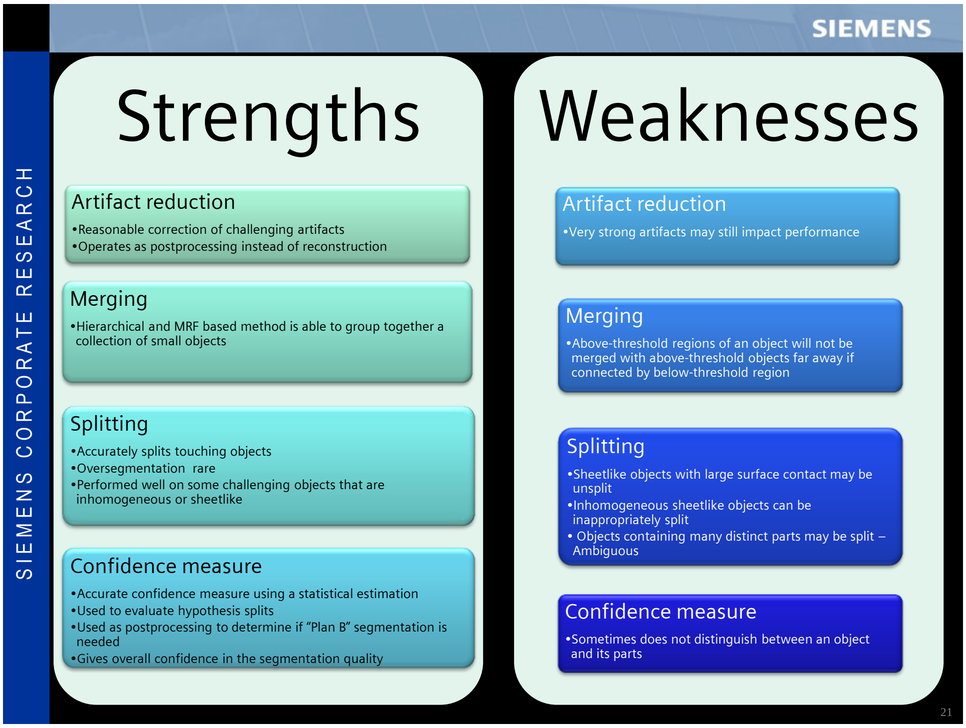
Quantitative - Automated confidence measure



20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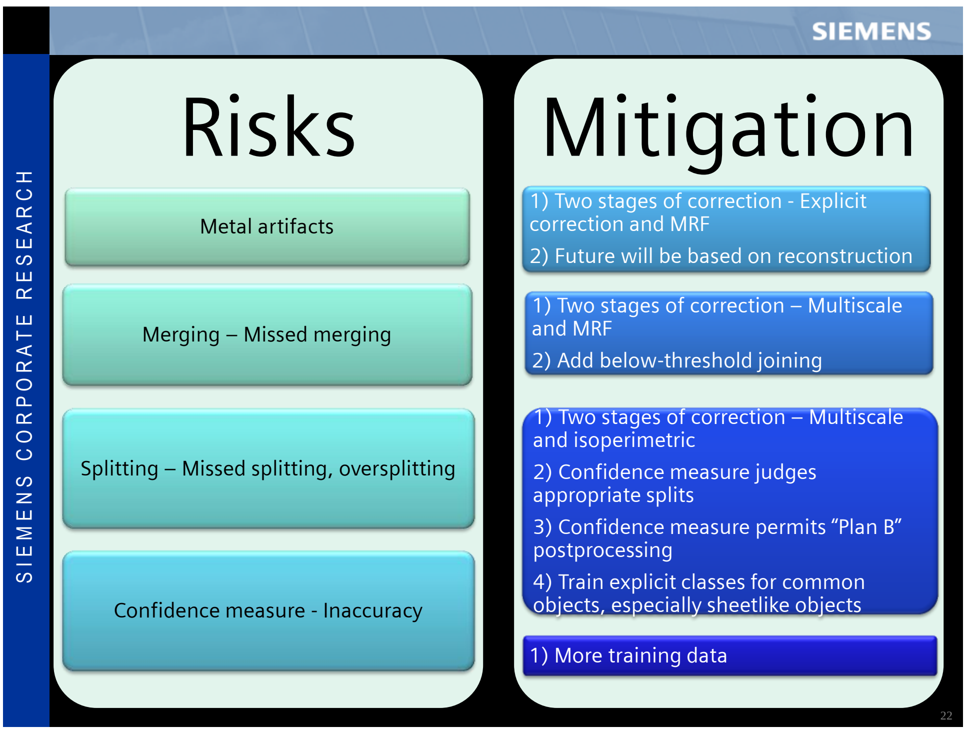
Strengths
Artifact reduction
•Reasonable correction of challenging artifacts
•Operates as postprocessing instead of reconstruction
Merging
•Hierarchical and MRF based method is able to group together a collection of small objects
Splitting
•Accurately splits touching objects
•Oversegmentation rare
•Performed well on some challenging objects that are inhomogeneous or sheetlike
Confidence measure
•Accurate confidence measure using a statistical estimation
•Used to evaluate hypothesis splits
•Used as postprocessing to determine if "Plan B" segmentation is needed
•Gives overall confidence in the segmentation quality
Weaknesses
Artifact reduction
•Very strong artifacts may still impact performance
Merging
•Above-threshold regions of an object will not be merged with above-threshold objects far away if connected by below-threshold region
Splitting
•Sheetlike objects with large surface contact may be unsplit
•Inhomogeneous sheetlike objects can be inappropriately split
• Objects containing many distinct parts may be split – Ambiguous
Confidence measure
•Sometimes does not distinguish between an object and its parts
21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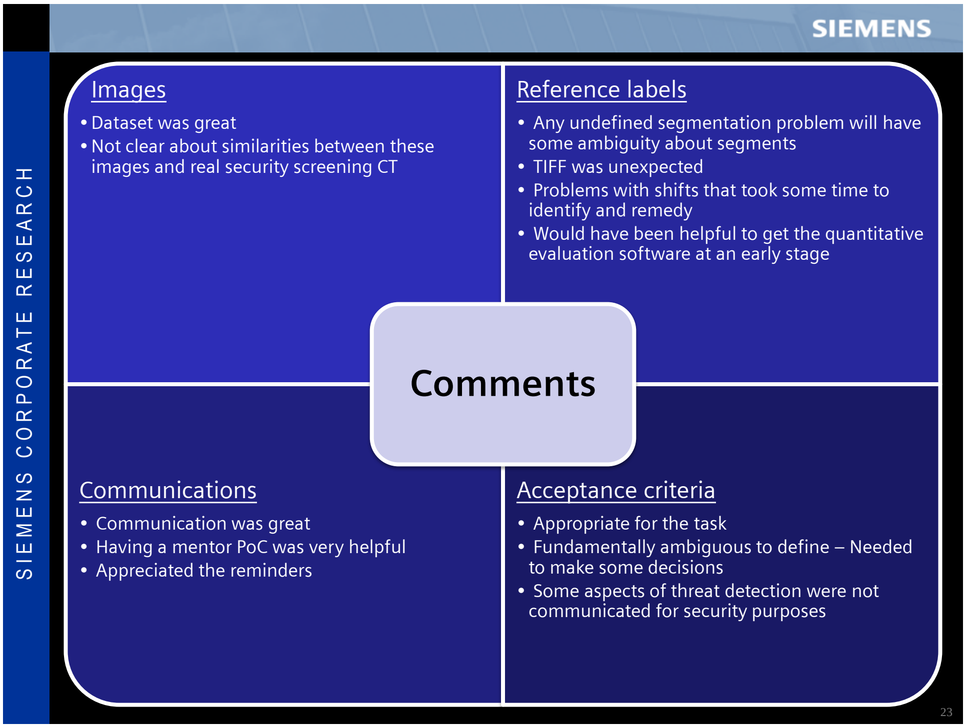
Risks
Metal artifacts
Merging – Missed merging
Splitting – Missed splitting, oversplitting
Confidence measure - Inaccuracy
Mitigation
1) Two stages of correction - Explicit correction and MRF
2) Future will be based on reconstruction
1) Two stages of correction – Multiscale and MRF
2) Add below-threshold joining
1) Two stages of correction – Multiscale and isoperimetric
2) Confidence measure judges appropriate splits
3) Confidence measure permits "Plan B" postprocessing
4) Train explicit classes for common objects, especially sheetlike objects
1) More training data
22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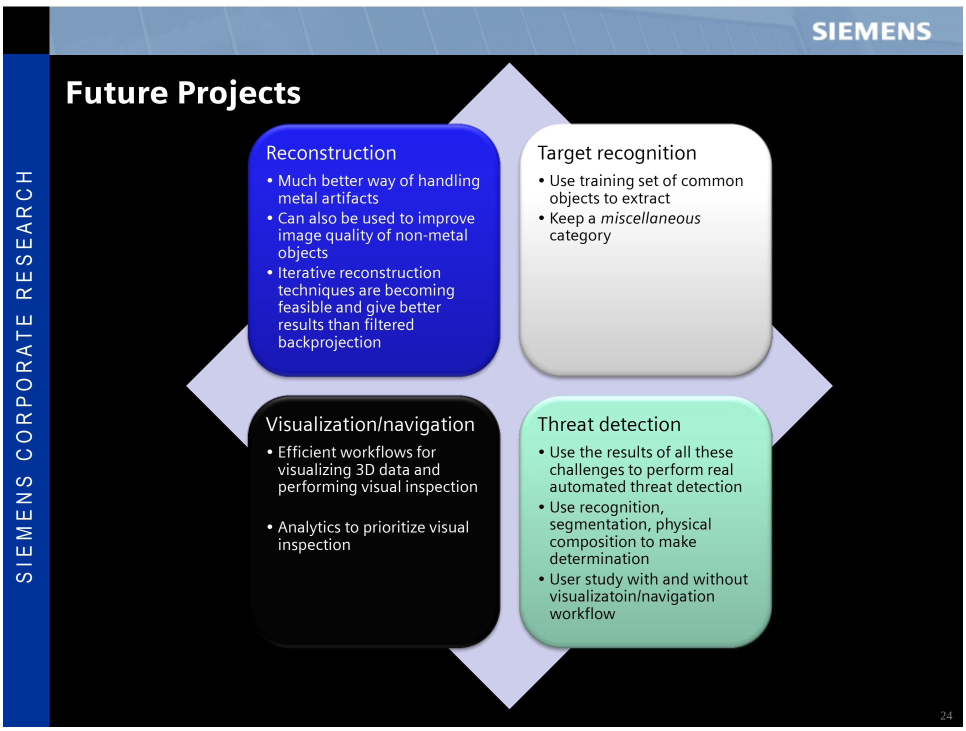
Images
• Dataset was great
• Not clear about similarities between these images and real security screening CT
Reference labels
• Any undefined segmentation problem will have some ambiguity about segments
• TIFF was unexpected
• Problems with shifts that took some time to identify and remedy
• Would have been helpful to get the quantitative evaluation software at an early stage
Comments
Communications
• Communication was great
• Having a mentor PoC was very helpful
• Appreciated the reminders
Acceptance criteria
• Appropriate for the task
• Fundamentally ambiguous to define – Needed to make some decisions
• Some aspects of threat detection were not communicated for security purposes
23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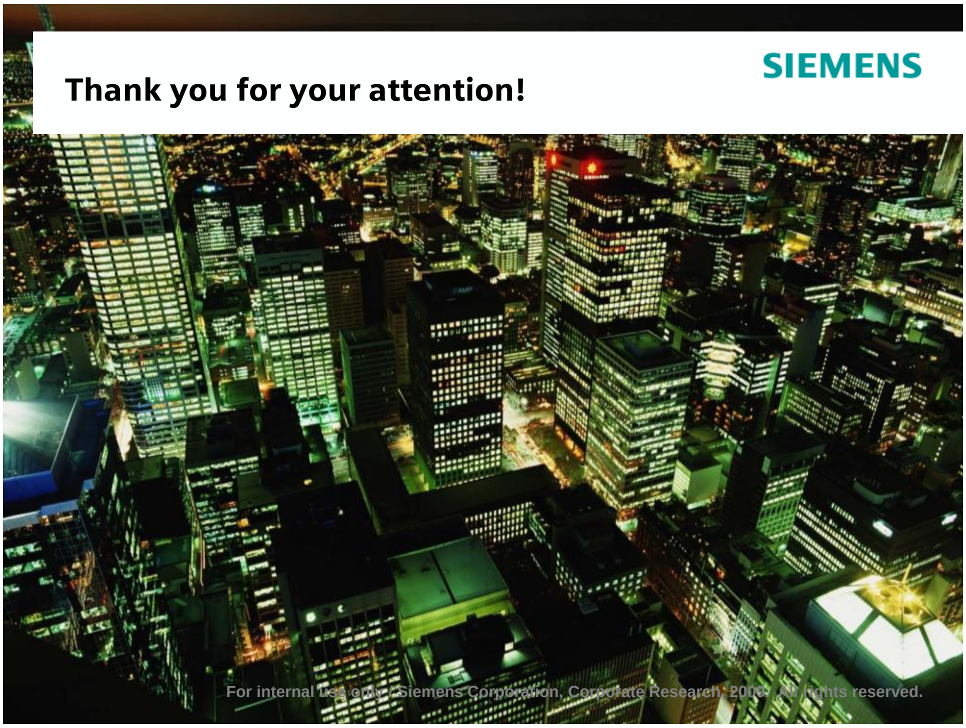
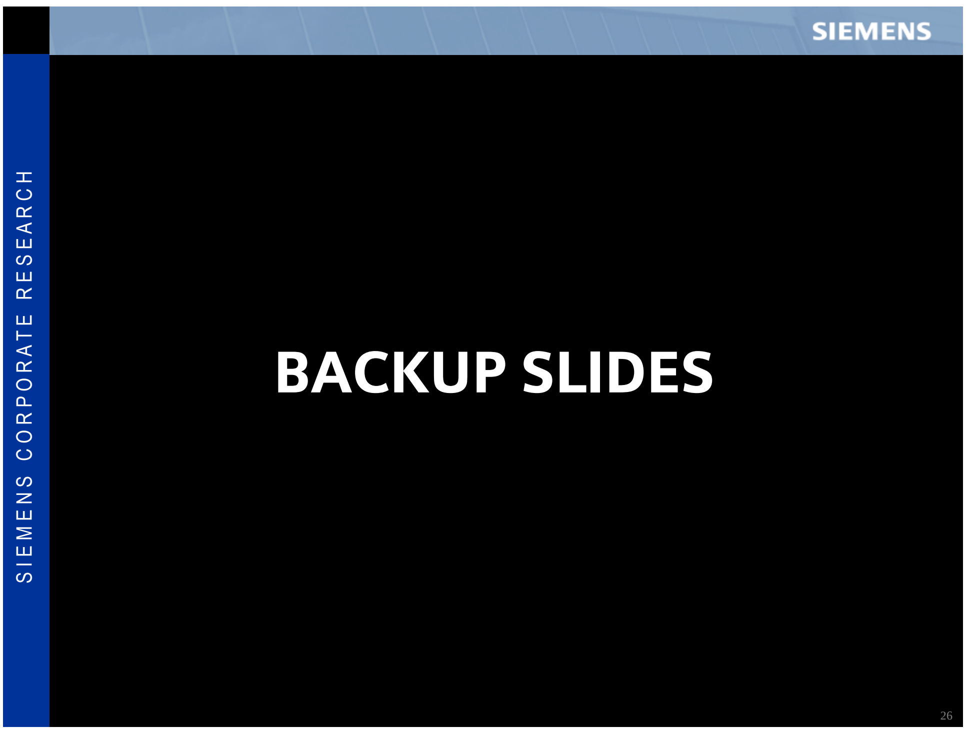
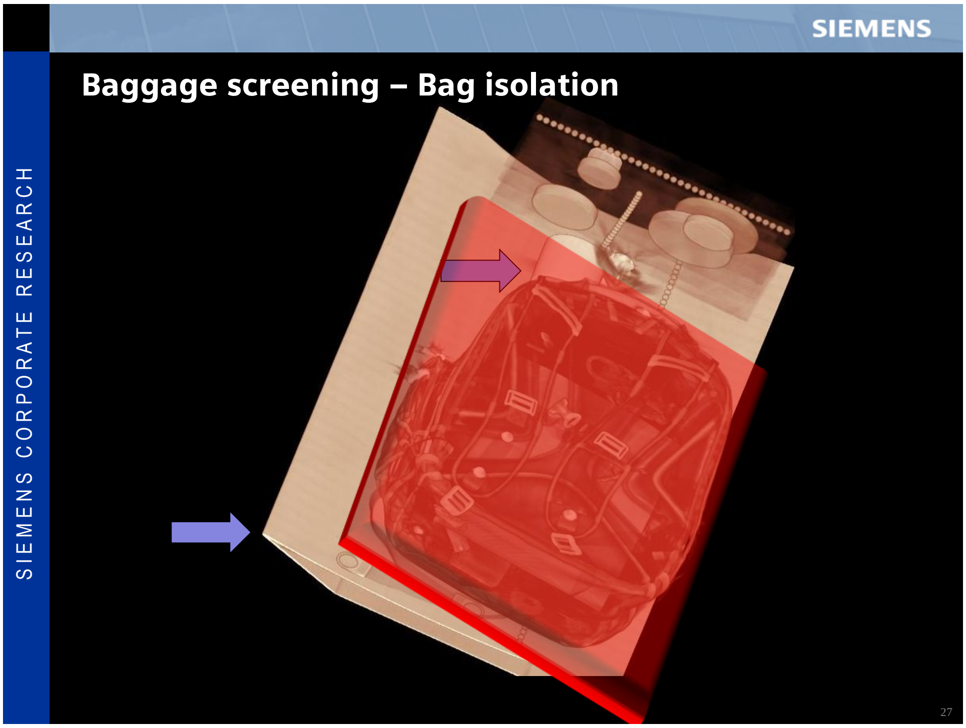
Future Projects
Reconstruction
• Much better way of handling metal artifacts
• Can also be used to improve image quality of non-metal objects
• Iterative reconstruction techniques are becoming feasible and give better results than filtered backprojection
Target recognition
• Use training set of common objects to extract
• Keep a *miscellaneous* category
Visualization/navigation
• Efficient workflows for visualizing 3D data and performing visual inspection
• Analytics to prioritize visual inspection
Threat detection
• Use the results of all these challenges to perform real automated threat detection
• Use recognition, segmentation, physical composition to make determination
• User study with and without visualizatoin/navigation workflow
24


Thank you for your attention!
SIEMENS
For internal use only / Siemens Corporation, Corporate Research, 2008. All rights reserved.


SIEMENS
SIEMENS CORPORATE RESEARCH
BACKUP SLIDES
26


SIEMENS
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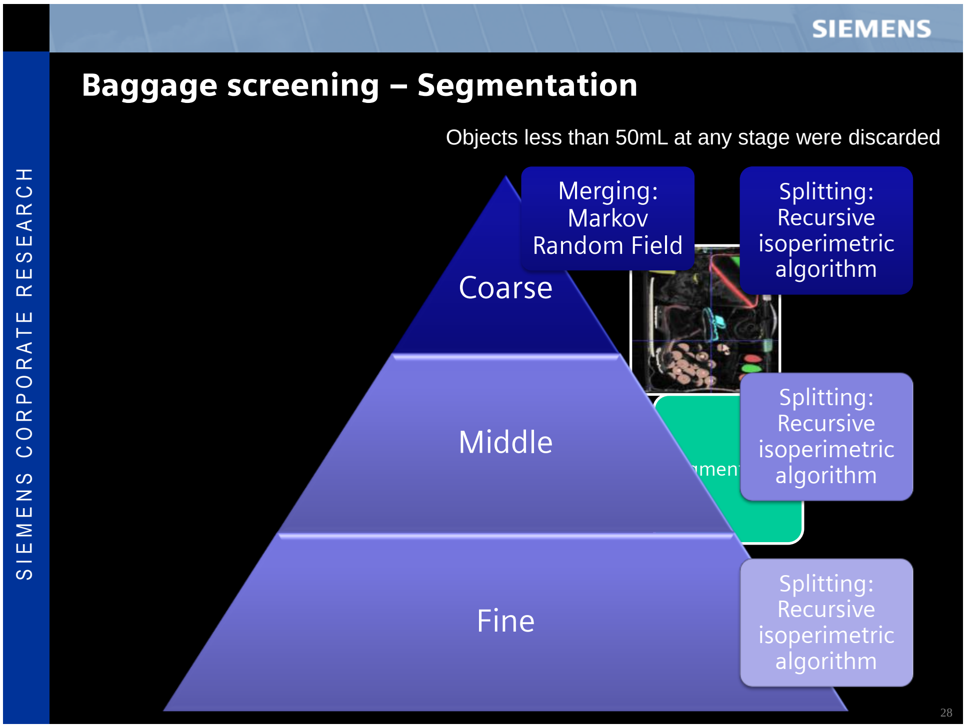
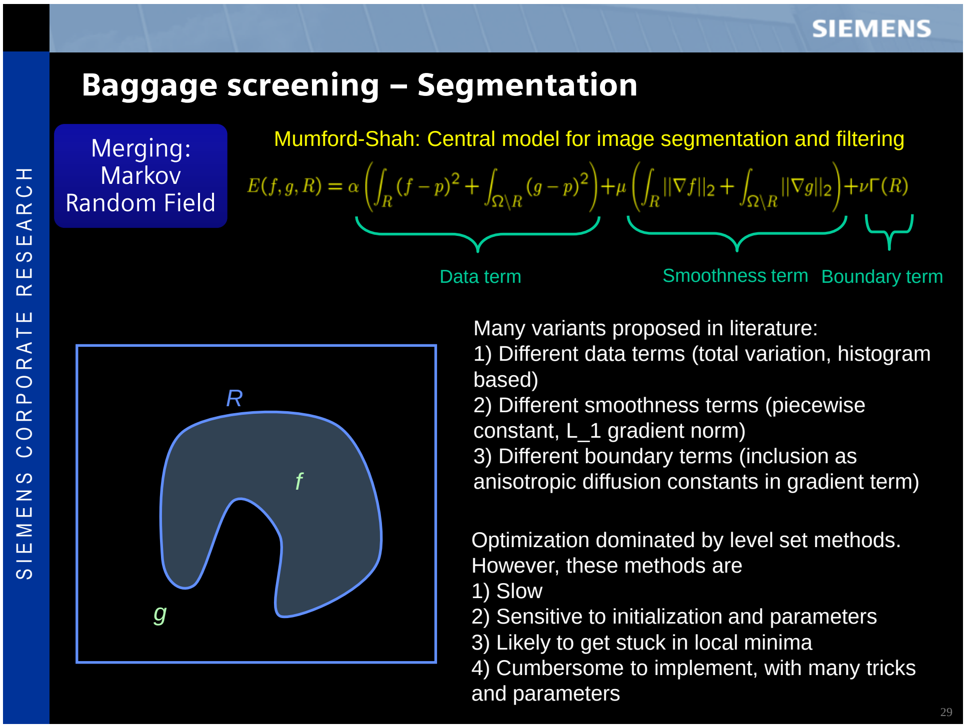
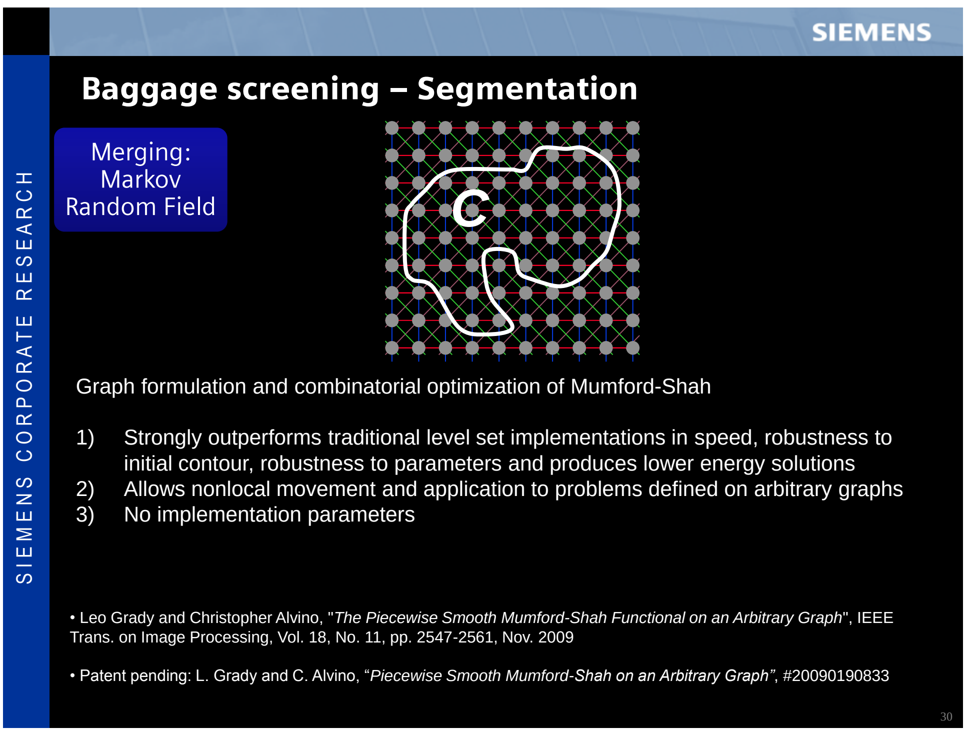
Baggage screening – Bag isolation
27


SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Objects less than 50mL at any stage were discarded
Merging: Markov Random Field
Splitting: Recursive isoperimetric algorithm
Coarse
Middle
Splitting: Recursive isoperimetric algorithm
Fine
Splitting: Recursive isoperimetric algorithm
28


SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Merging: Markov Random Field
Mumford-Shah: Central model for image segmentation and filtering
$E(f,g,R) = \alpha\left(\int_R (f-p)^2 + \int_{\Omega\setminus R}(g-p)^2\right) + \mu\left(\int_R \|\nabla f\|_2 + \int_{\Omega\setminus R}\|\nabla g\|_2\right) + \nu\Gamma(R)$
Data term
Smoothness term
Boundary term
R
f
g
Many variants proposed in literature:
1) Different data terms (total variation, histogram based)
2) Different smoothness terms (piecewise constant, L_1 gradient norm)
3) Different boundary terms (inclusion as anisotropic diffusion constants in gradient term)
Optimization dominated by level set methods. However, these methods are
1) Slow
2) Sensitive to initialization and parameters
3) Likely to get stuck in local minima
4) Cumbersome to implement, with many tricks and parameters
29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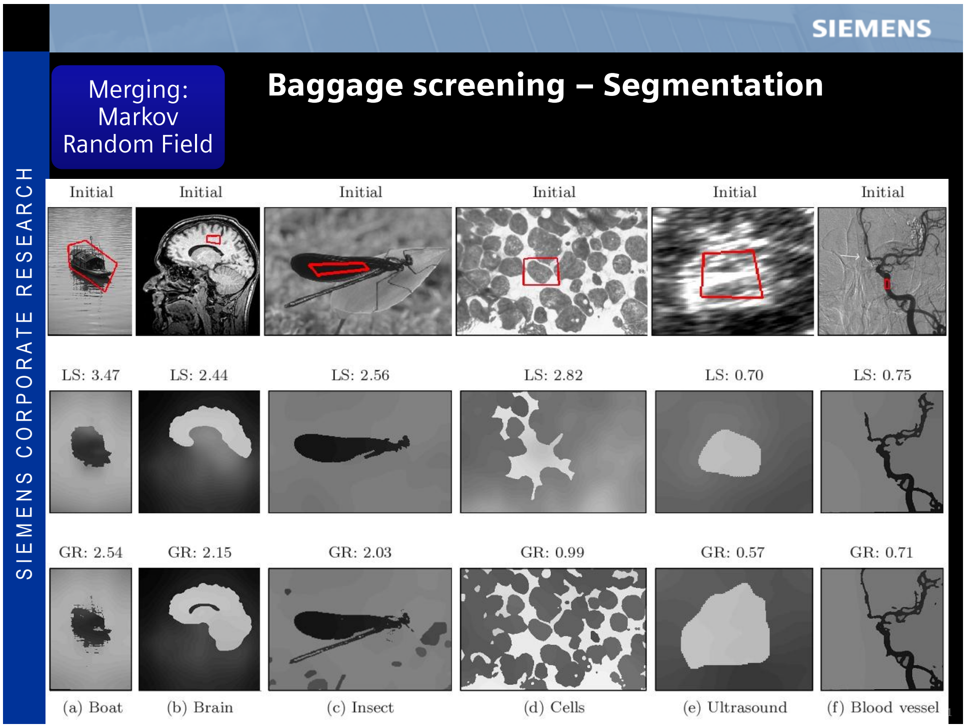
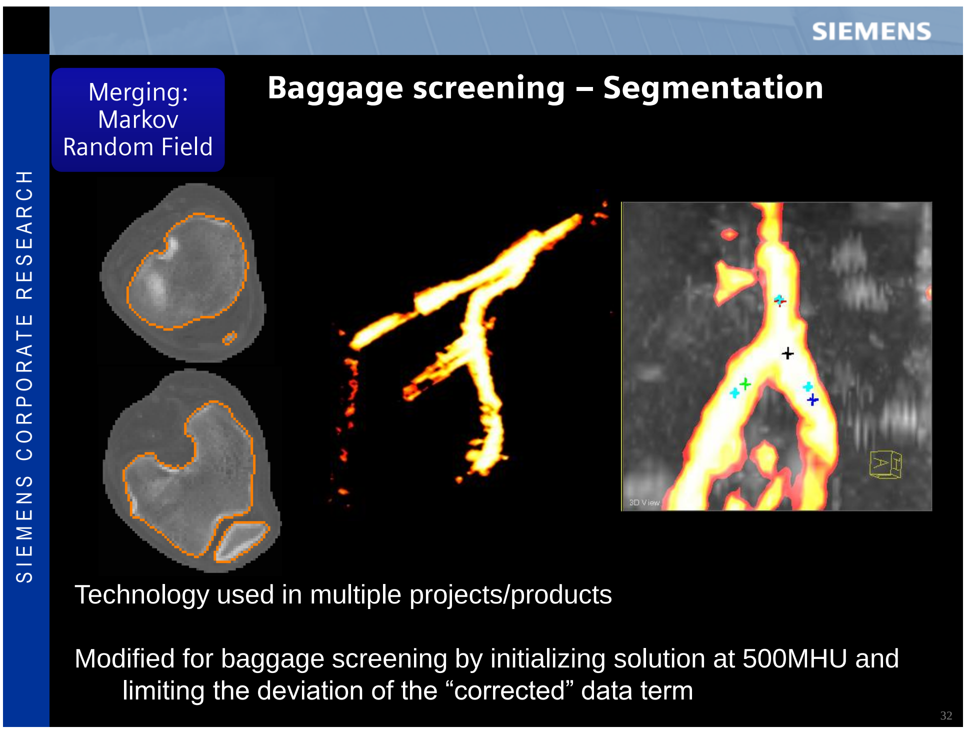
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Merging: Markov Random Field
C
Graph formulation and combinatorial optimization of Mumford-Shah
1) Strongly outperforms traditional level set implementations in speed, robustness to initial contour, robustness to parameters and produces lower energy solutions
2) Allows nonlocal movement and application to problems defined on arbitrary graphs
3) No implementation parameters
• Leo Grady and Christopher Alvino, "The Piecewise Smooth Mumford-Shah Functional on an Arbitrary Graph", IEEE Trans. on Image Processing, Vol. 18, No. 11, pp. 2547-2561, Nov. 2009
• Patent pending: L. Grady and C. Alvino, "Piecewise Smooth Mumford-Shah on an Arbitrary Graph", #20090190833
30


SIEMENS
SIEMENS CORPORATE RESEARCH
Merging: Markov Random Field
Baggage screening – Segmentation
Initial
Initial
Initial
Initial
Initial
Initial
LS: 3.47
LS: 2.44
LS: 2.56
LS: 2.82
LS: 0.70
LS: 0.75
GR: 2.54
GR: 2.15
GR: 2.03
GR: 0.99
GR: 0.57
GR: 0.71
(a) Boat
(b) Brain
(c) Insect
(d) Cells
(e) Ultrasound
(f) Blood vessel


SIEMENS
SIEMENS CORPORATE RESEARCH
Merging: Markov Random Field
Baggage screening – Segmentation
Technology used in multiple projects/products
Modified for baggage screening by initializing solution at 500MHU and limiting the deviation of the “corrected” data term
32

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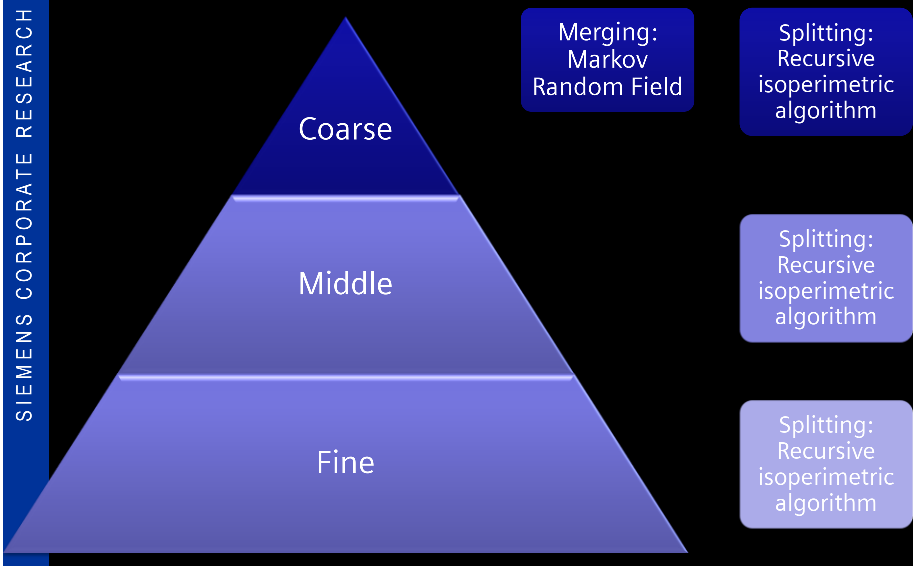
Baggage screening – Segmentation



33

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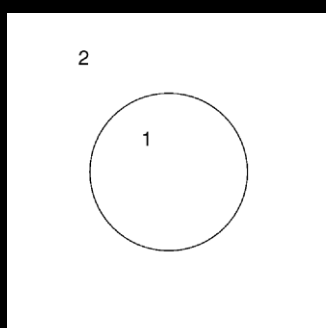
Baggage screening – Segmentation

Splitting: Recursive isoperimetric algorithm

Motivated from the classical isoperimetric problem: For a given volume, what is the shape with minimum perimeter?

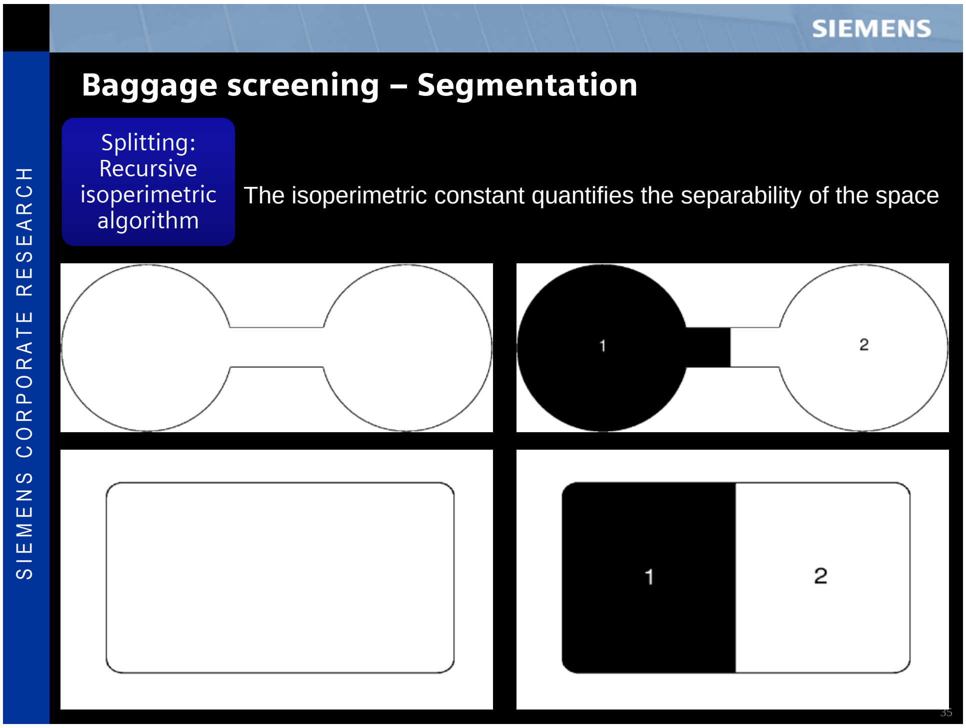


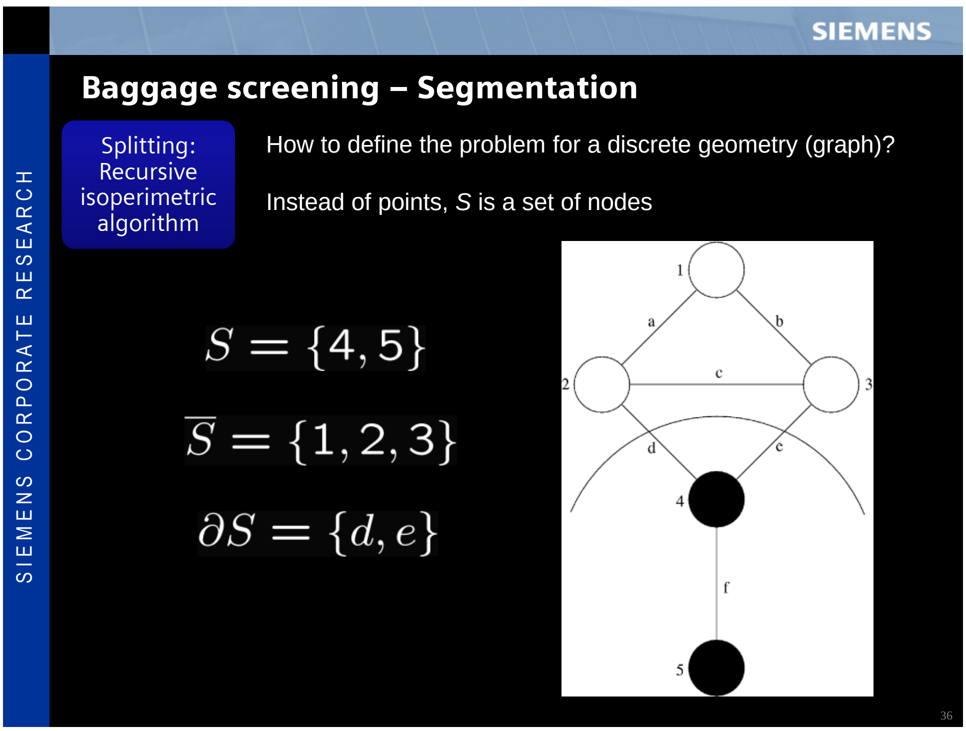
Enclosing a volume with a boundary may be considered as a *separation* of the space

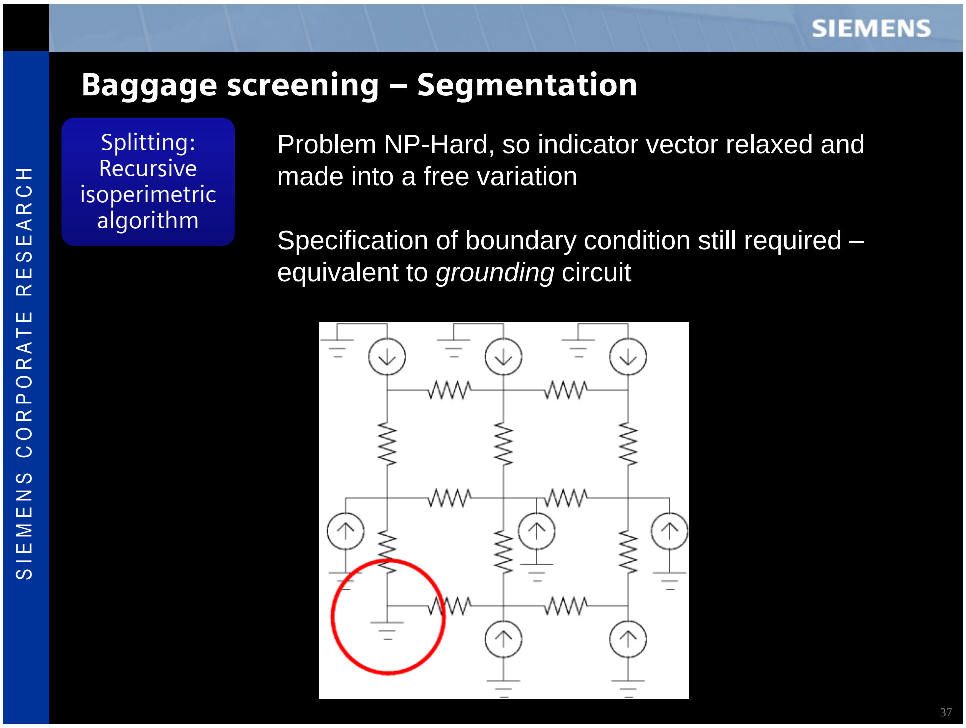
• Leo Grady and Eric L. Schwartz, "*Isoperimetric Partitioning: A new algorithm for graph partitioning*", SIAM Journal on Scientific Computing, vol. 27, no. 6, pp. 1844-1866, June 2006.

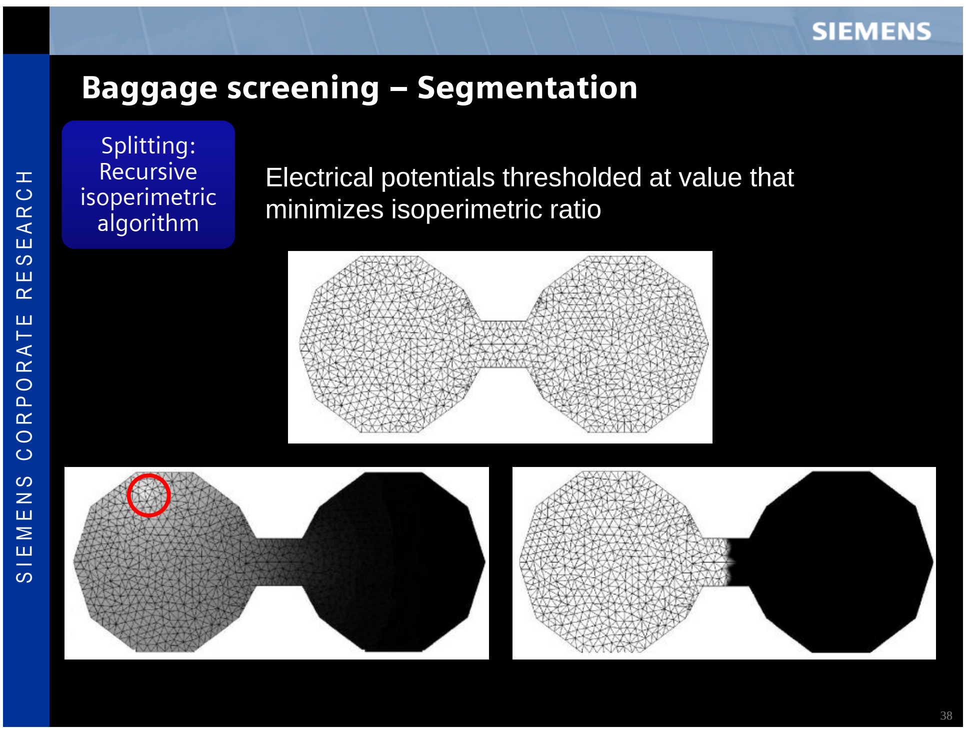
• Leo Grady and Eric L. Schwartz, "*Isoperimetric Graph Partitioning for Image Segmentation*", IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 28, no. 3, pp. 469-475, March 2006

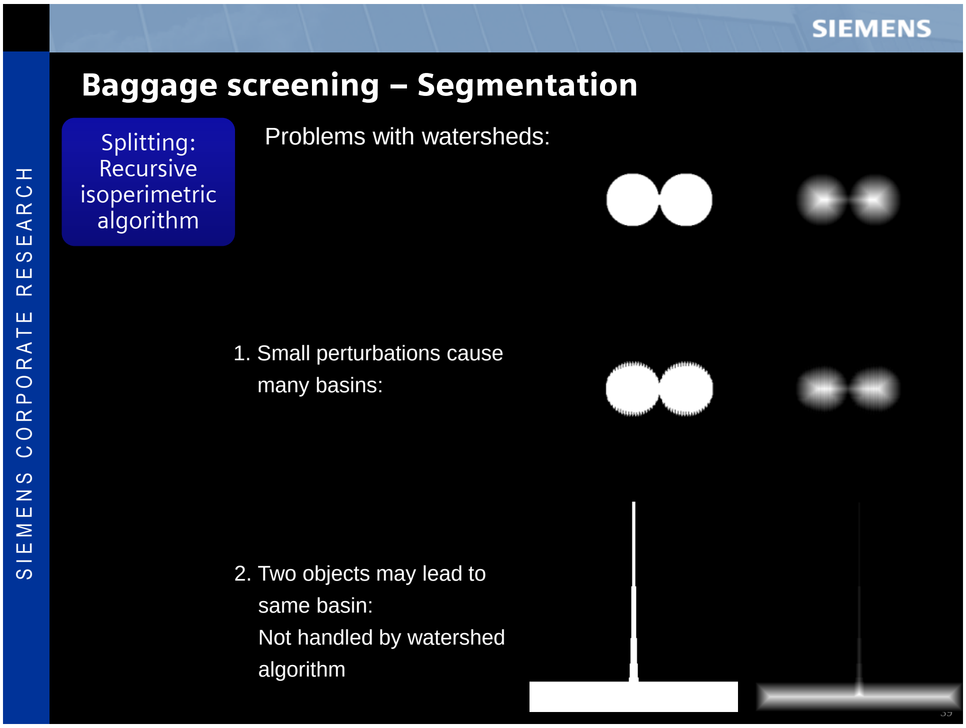
34

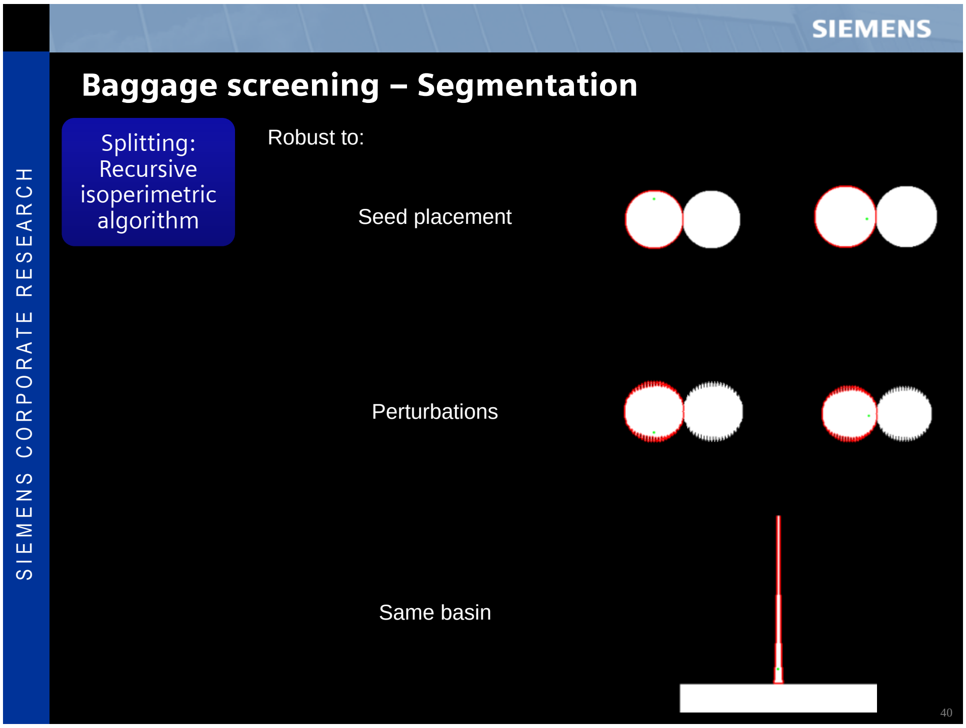

SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Splitting: Recursive isoperimetric algorithm
The isoperimetric constant quantifies the separability of the space
1
2
1
2

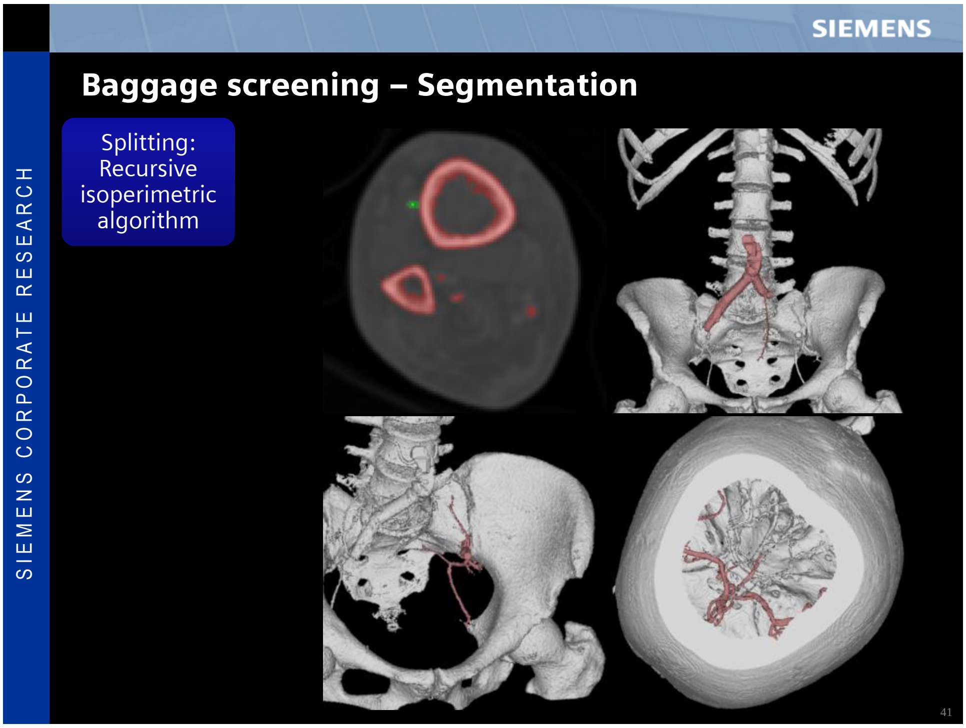

SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Splitting: Recursive isoperimetric algorithm
How to define the problem for a discrete geometry (graph)?
Instead of points, S is a set of nodes
$S = \{4, 5\}$
$\overline{S} = \{1, 2, 3\}$
$\partial S = \{d, e\}$
1
2
3
4
5
a
b
c
d
e
f


SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Splitting: Recursive isoperimetric algorithm
Problem NP-Hard, so indicator vector relaxed and made into a free variation
Specification of boundary condition still required – equivalent to *grounding* circuit
37

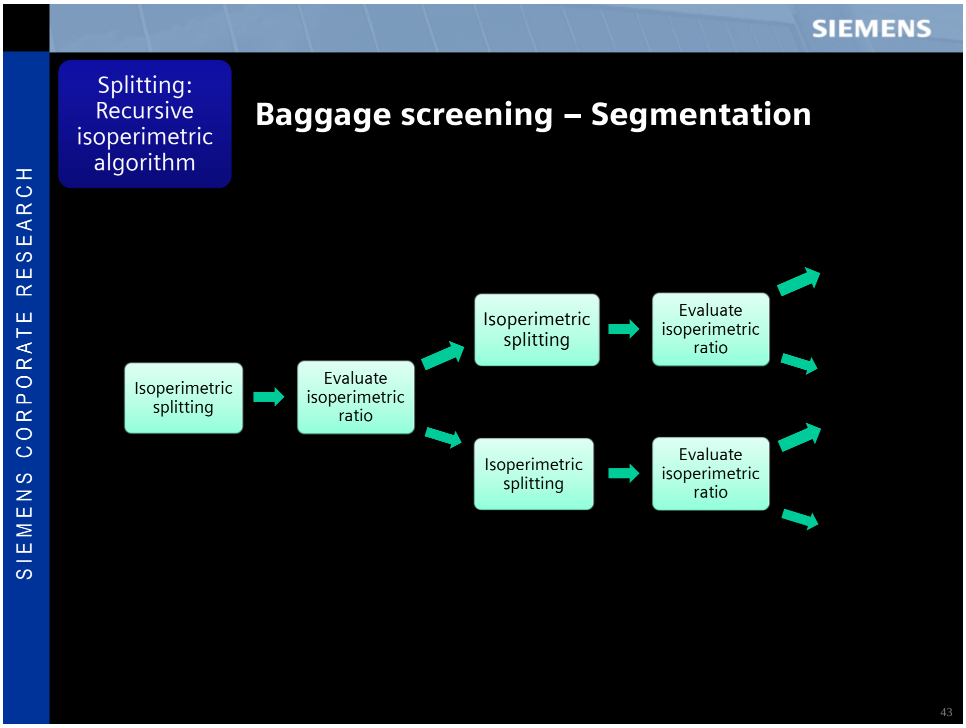

SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Splitting: Recursive isoperimetric algorithm
Electrical potentials thresholded at value that minimizes isoperimetric ratio
38

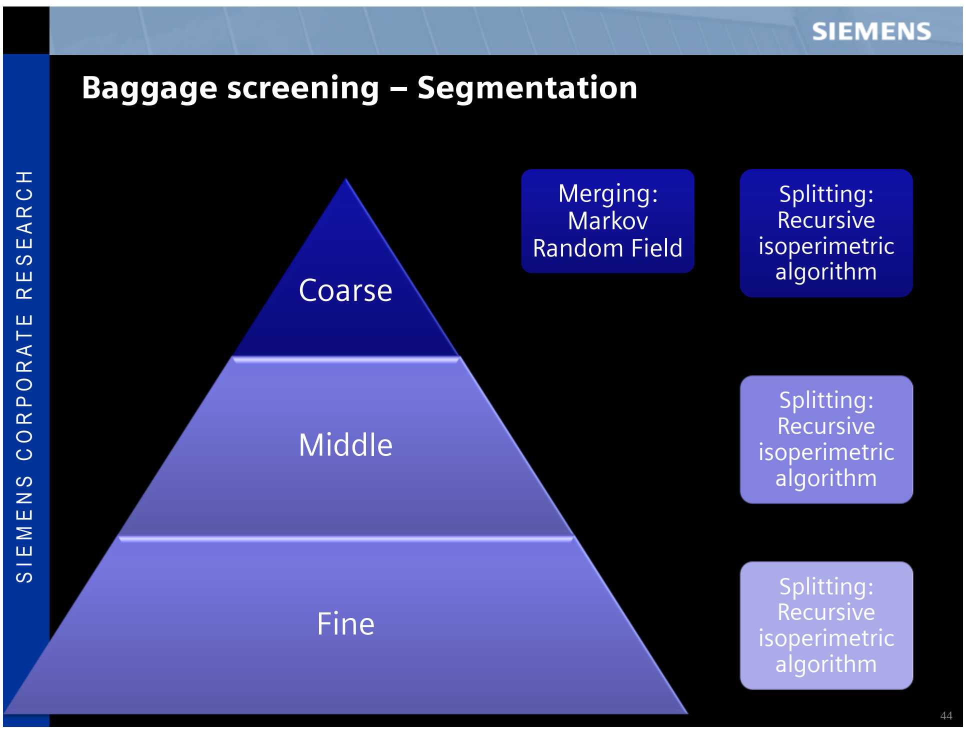

SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Splitting: Recursive isoperimetric algorithm
Problems with watersheds:
1. Small perturbations cause many basins:
2. Two objects may lead to same basin:
Not handled by watershed algorithm

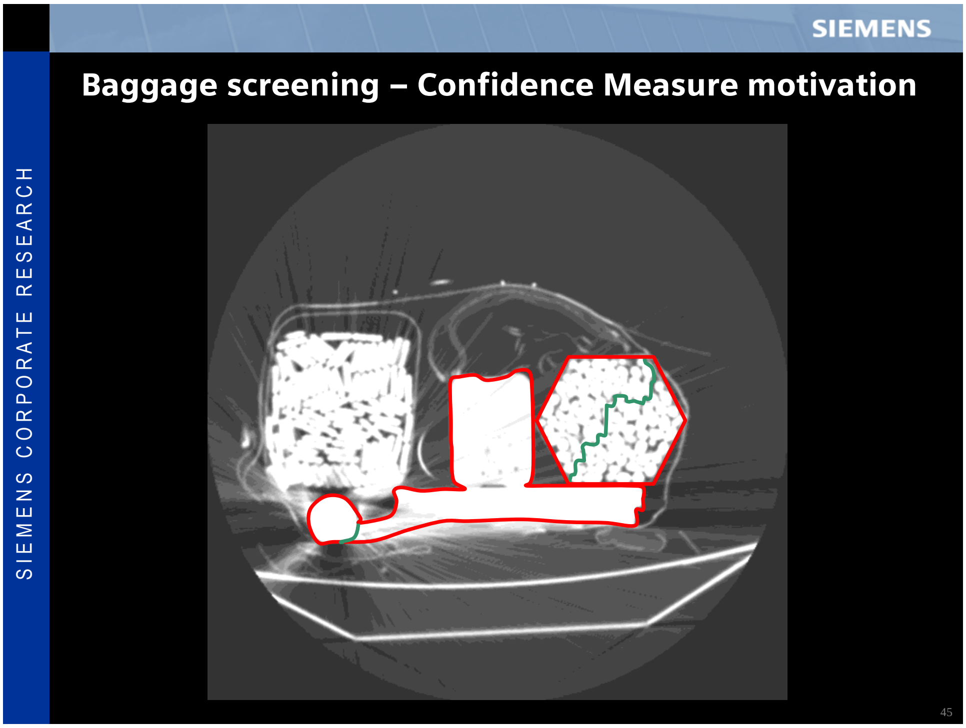

SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Splitting: Recursive isoperimetric algorithm
Robust to:
Seed placement
Perturbations
Same basin
40

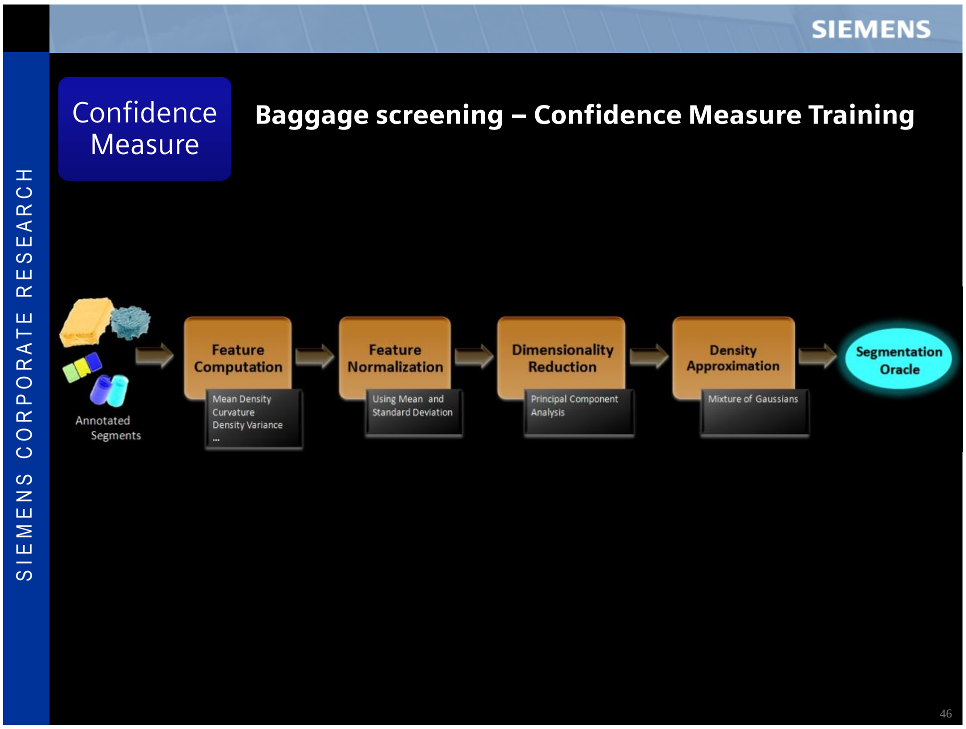

SIEMENS
Baggage screening – Segmentation
Splitting: Recursive isoperimetric algorithm
SIEMENS CORPORATE RESEARCH
41

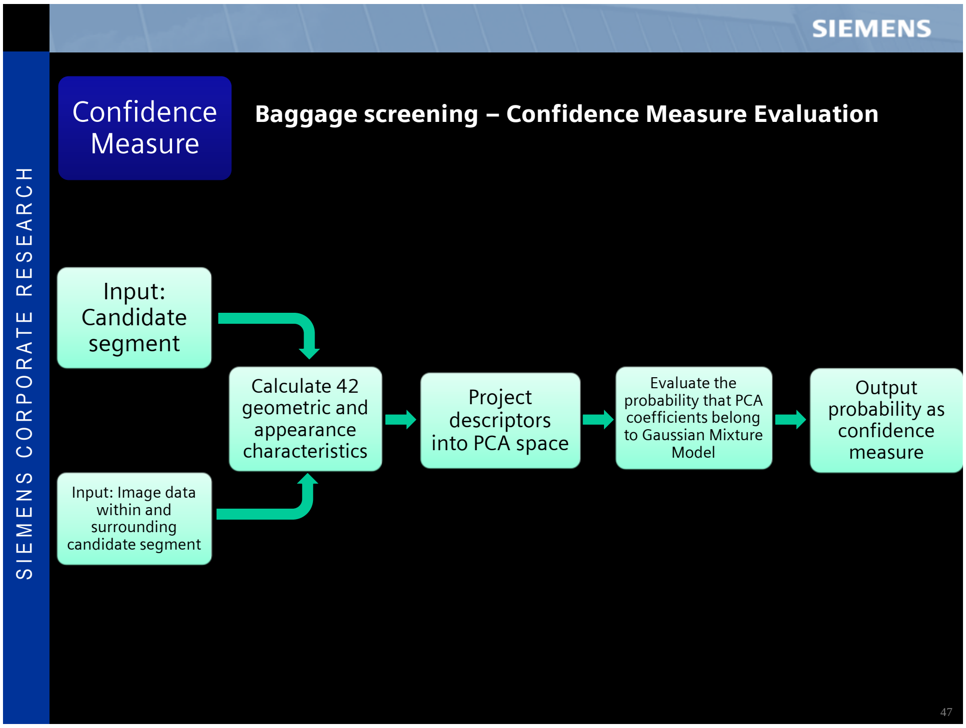

SIEMENS
Splitting: Recursive isoperimetric algorithm
Baggage screening – Segmentation
SIEMENS CORPORATE RESEARCH
42

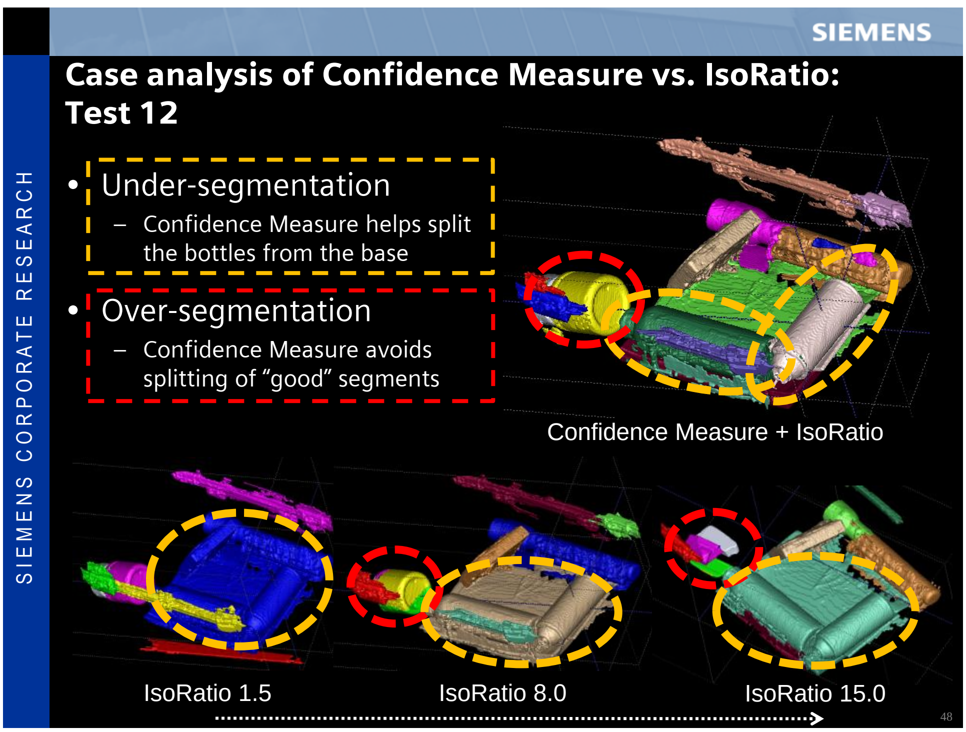

SIEMENS
SIEMENS CORPORATE RESEARCH
Splitting: Recursive isoperimetric algorithm
Baggage screening – Segmentation
Isoperimetric splitting
Evaluate isoperimetric ratio
Isoperimetric splitting
Evaluate isoperimetric ratio
Isoperimetric splitting
Evaluate isoperimetric ratio
43

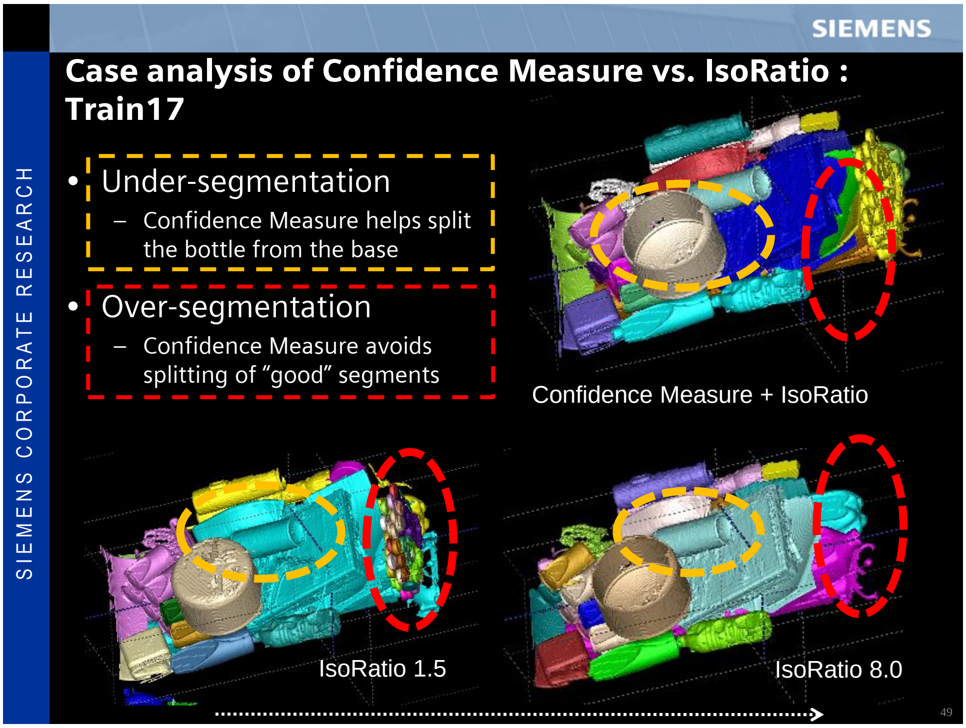

SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Segmentation
Coarse
Middle
Fine
Merging: Markov Random Field
Splitting: Recursive isoperimetric algorithm
Splitting: Recursive isoperimetric algorithm
Splitting: Recursive isoperimetric algorithm
44

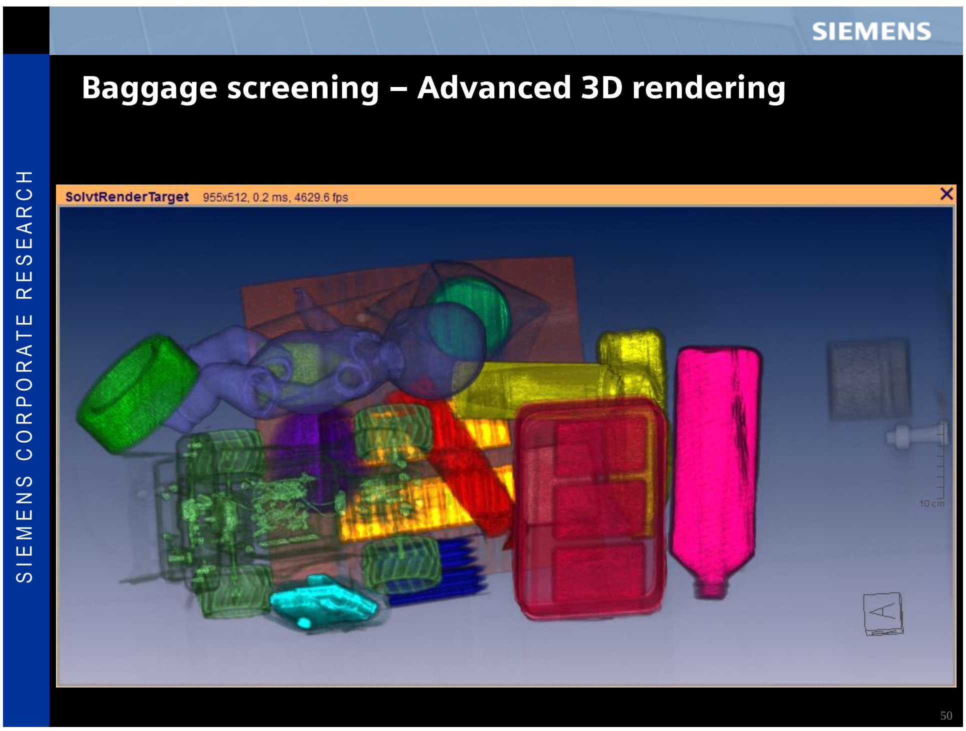

SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Confidence Measure motivation
45

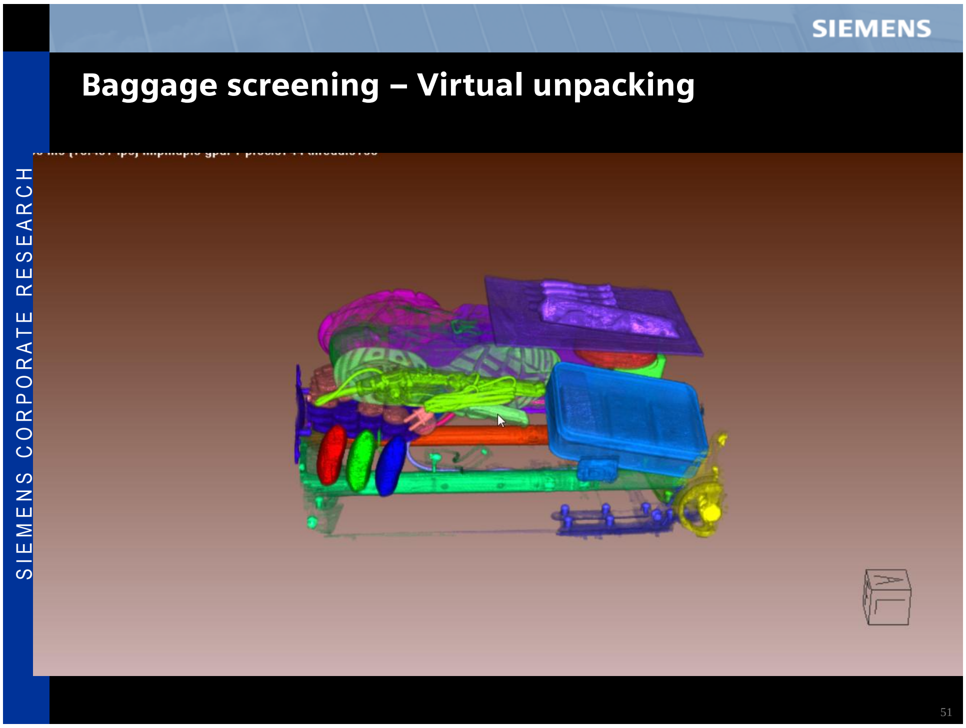

SIEMENS
SIEMENS CORPORATE RESEARCH
Confidence Measure
Baggage screening – Confidence Measure Training
Annotated Segments
Feature Computation
Mean Density
Curvature
Density Variance
...
Feature Normalization
Using Mean and Standard Deviation
Dimensionality Reduction
Principal Component Analysis
Density Approximation
Mixture of Gaussians
Segmentation Oracle
46


SIEMENS
SIEMENS CORPORATE RESEARCH
Confidence Measure
Baggage screening – Confidence Measure Evaluation
Input: Candidate segment
Input: Image data within and surrounding candidate segment
Calculate 42 geometric and appearance characteristics
Project descriptors into PCA space
Evaluate the probability that PCA coefficients belong to Gaussian Mixture Model
Output probability as confidence measure
47


SIEMENS
SIEMENS CORPORATE RESEARCH
Case analysis of Confidence Measure vs. IsoRatio: Test 12
• Under-segmentation
– Confidence Measure helps split the bottles from the base
• Over-segmentation
– Confidence Measure avoids splitting of "good" segments
Confidence Measure + IsoRatio
IsoRatio 1.5
IsoRatio 8.0
IsoRatio 15.0
48


SIEMENS
SIEMENS CORPORATE RESEARCH
Case analysis of Confidence Measure vs. IsoRatio : Train17
• Under-segmentation
– Confidence Measure helps split the bottle from the base
• Over-segmentation
– Confidence Measure avoids splitting of "good" segments
Confidence Measure + IsoRatio
IsoRatio 1.5
IsoRatio 8.0
49


SIEMENS
SIEMENS CORPORATE RESEARCH
Baggage screening – Advanced 3D rendering
SolvtRenderTarget 955x512, 0.2 ms, 4629.6 fps
10 cm
50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Baggage screening – Virtual unpacking
SIEMENS CORPORATE RESEARCH
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9.2 Other Appendix Material

9.2.1 Appendix: "Data acquisition and segmentation for final report," Alyssa White and Rick Moore.

9.2.1.1 Dataset design

About 75 million international and 650 million domestic enplanements occur annually (FAA website, March, 2010), many with checked baggage. Selecting a representative set of luggage across the parameters of size, material, age, frame, aspect-ratio, etc. to scan for (task order1) is required. The range of legally packable items is similarly broad over parameters of material, size, geometry, density, phase, aspect-ratio, among others. The ALERT center procured the following luggage for this project:

Bag 7001 – Red Hard Shell Case

Bag 7002 - Backpack

Bag 7003 – Medium Black Roller

Bag 7004 - Blue Duffle

Bag 7005 – Water-Proof Backpack

Bag 7006 – Large Black Roller

Bag 7007 – Laptop case

Bag 7008 - Cardboard Box

To pack the luggage ALERT procured the following items

Code	Desc	Code	Desc	Code	Desc	Code	Desc
2	clothes Iron	64	candle - glass	2081	small electronic	4057	laptop
3	toothpaste tube	65	Candle with lid	2082	Camera Tripod	5001	StainlessSteel containing water
4	Wooden frame	66	Shampoo	2083	tupperware - 3 pk	5002	Nalgene with Rice
5	Metal frame	67	conditioner	2084	Leather Jacket	5003	StainlessSteel containing Castor oil
6	Chocolate Bar 1	69	Rubber Sealant	2086	Clay block 1	5004	StainlessSteel containing Water
7	Chocolate Bar 2	70	Aerosol - Off!	2087	Clay block 2	5005	Nalgene containing water
8	RedHeelShoeL	71	Jewelry-earrings	2090	Butyl rubber sheet	5006	Rectangular Glass containing castor oil
9	RedHeelShoeR	72	Jeans-4-fold	2091	butyl rubber sheet 2	5007	StainlessSteel Vaccuum bottle with Water
10	Mens shoe-R	1000	toy doll - Potatoe Head	2092	neoprene rubber sheet	8010	Small Nylon
11	Mens shoe- L	1001	Palm680inLeatherCase	2093	neoprene rubber sheet 2	8011	small nylon 2
12	Mens Sneaker - R	1002	LCD-Clock-Cord	2094	Remote control car	8012	Clay disc 1
13	Mens Sneaker - L	1003	Large Flashlight	2097	Electrical Tape	8013	Clay disc 2
14	toy-robot	1004	smallMagLight	2098	jeans	8014	Large Nylon Disc 1
15	RedPurseAndContents	2001	Toothbrushes - 4 pk	2099	Box Cutter	8015	Large Nylong Disc 2
16	Purse-black	2002	water bottle 1	3001	Doll- baby snow white	8016	PVC Disc 1
17	Pot with lid	2003	Water bottle 2	3002	Digital Camera	8017	PVC Disc 2
18	Hair drier w. extension	2004	Water bottle 3	3003	Cereal - special K	8018	Urethane Foam Disc 1
19	Flat Iron	2005	Trail Mix	3005	48 pk batteries	8019	Urethane Foam Disc 2
21	aerosol-metallic paint	2006	Play doh	3006	Hard Drive	8020	butyl rubber sheet (mid)
22	Boots-R	2007	Bird Book w/sound	3007	Hard Drive w/ USB	8021	butyl rubber sheet (mid)
23	Boots-L	2008	Gel pad	4001	Maple Syrup	8022	butyl rubber sheet (thin)
29	BailOSocks2	2009	Liquid Lotion	4002	peroxide	8023	butyl rubber sheet (thin)
31	BailOSocks 1	2011	jewelry-bracelets	4003	Rubbing Alcohol	8024	Neoprene rubber sheet (thin)
50	Yoga Mat	2012	Edge shaving cream	4004	acetone	8025	Neoprene rubber sheet (thin)
51	2Liter MtnDew	2013	Jerkey	4005	Motor oil	8026	Neoprene rubber sheet (mid)
53	6pkSoda	2050	jelly Beans	4006	Motor oil	8027	Neoprene rubber sheet (mid)
54	CD's	2051	honey	4020	rubbing alcohol	8028	Neoprene rubber sheet (thick)
56	8 pk diet coke	2060	steel bolt	4021	peroxide	8029	butyl rubber sheet (thick)
57	2LiterPepsi	2061	Piece of steel 1	4050	playing cards 1	9993	Magazine - GH
58	Skin Cream	2062	Piece of steel 2	4051	playing cards 2	9994	Elle Magazine
59	Duct Tape	2063	Cell phone 2	4052	projector	9995	Skip Bo game
60	Crayons	2064	jewelry-necklace/earrings set	4053	gel pad 2	9996	BraBlackSequin
61	Petroleum Jelly	2065	jewerly-bracelets	4054	ac adapter- 1-black	9997	WhitePlainBra
62	Bar Soap	2066	jewelry earrings	4055	ac adapter-2-grey	9998	Paperback-HighClay 1
63	Candles - tealight	2080	Radio with cord	4056	4pk scotch tape	9999	Paperback-HighClay 2

Figure 1: List of objects contained within the CT datasets.

9.2.1.2 Creation of datasets

ALERT characterized all of the objects that went into the datasets. Each bag and each object in each bag were identified (labeled with a vector and serial number), measured (length, width, height), and density-characterized. Each object was also scanned in isolation following the acquisition of the datasets. The bag was introduced into the CT scanner in multiple orientations (upright, sidewise, skew, invert). It was also disrupted and rescanned in multiple orientations. Known reference phantoms composed of reference materials were scanned with each dataset, to serve as a calibration and to monitor image quality throughout the scanning process. At the Vendor, unpacking of the bags was videotaped after imaging. The Dataset Groups contained images of luggage that present a range of difficult segmentation issues (varying kinds and number of objects, proximity (relative position), and purposeful obfuscation).

We acquired datasets over a 7 month span beginning in September of 2010 and extending to March of 2011. These datasets were put together using a combination of 8 bags and approximately 145 items to create a variety of luggage combinations which represent a range of difficulties. The datasets were all acquired at the same vendor using a medical CT scanner at a resolution of 1mm.

Any suitcase contains 8-25 of these objects, plus filler objects such as clothing (e.g. sweaters). Some bags are packed randomly, while others were packed to create certain situations. All objects have been measured (x, y, z) weighed, physically labeled with a code number, and photographed. An example of the labeling is demonstrated in the image below:

Figure 2: Photo of large flashlight, object #1003 with yellow physical label.

The process to collect the datasets at the vendor is as follows:

1. Researcher packs objects into bags at ALERT.
2. Researcher documents which objects are packed into which bags as they are being packed
3. Researcher loads bags and travels to the vendor location
4. At the vendor, researcher images first bag in orientation #1-n, taking photo of orientation before each scan.
5. After all images of bag 1 are acquired, researcher removes bag from scanner and takes video of the unpacking of the bag, careful to capture position of objects within the bag.
6. If session involves repacking of the bag with same objects in more challenging positions, researcher repacks bag and repeats steps 4-5.
7. Repeat steps 4-5 (6 If necessary) for all bags brought to the Vendor.
8. Researcher brings bags back to ALERT, unpacks and returns objects to storage location.

9.2.1.3 Details of data acquisition

On October 14, 2010, Rick Moore (affiliated with MGH, subcontractor responsible for data collection) collected a number of test datasets at the vendor. He used 2 different bags to collect these sets – the

Red Hard Shell bag 7001 and the Backpack 7002. There were 15 items in each bag; none of these were the geometric objects. Of these test datasets, 9 were segmented and prepared for use in the Qualification Dataset to be sent out to all researchers who would sign our NDA. Only 2 of these 9 resulted in the Qualification dataset.

- CT_15.28.8 – RedHardShell, Packed, (0,0) orientation.
- CT_17.37.5 – Backpack, Packed, (0,0) orientation.

On January 6, 2011, Alyssa White (affiliated with MGH, subcontractor responsible for data collection) collected 28 datasets at the vendor. She used 7 different bags (bag numbers 7001-7007) and collected four datasets on each bag. There were 10-21 items in each bag; 2 geometric objects were incorporated into these sets. Bag 7003 and bag 7006 each contained one geometric object, therefore 8 of the 28 datasets contains a geometric object. Of these 28, 24 have been segmented and sent to the chosen participants. Twelve were included in the Training Set, another 6 in the Validation set, and 6 others in the Evaluation set. Four of the Datasets acquired are not being used at this time. Table n shows the details of the 28 datasets collected, while table n+1 shows how the 24 datasets used were separated between the Training, Validation and Evaluation sets. Notice that we chose to incorporate similar bags in each of the 3 sets. I.e. The 4 RedHardShell scans, packed and repacked with the same objects, were separated 2:1:1 between the Training, validation and evaluations sets. This allows researchers to train on datasets similar to those they may be evaluated with later on in the program

Images Acquired on 1/6/2011

Bags	Desc	Condition	Orientation	CT file
7001	RedHardShell	Packed	(0,0)	10.34.46
7001	RedHardShell	Packed	(0,15)	10.55.57
7001	RedHardShell	Repacked	(0,0)	14.21.52
7001	RedHardShell	Repacked	(0,15)	14.30.20
7002	Backpack	Packed	(0,0)	11.11.25
7002	Backpack	Packed	(0,15)	11.19.3
7002	Backpack	Repacked	(0,0)	14.52.23
7002	Backpack	Repacked	(0,15)	14.58.5
7003	Small Black Roller	Packed	(0,0)	11.31.19
7003	Small Black Roller	Packed	(0,15)	11.50.30
7003	Small Black Roller	Repacked	(0,0)	15.3.7
7003	Small Black Roller	Repacked	(0,15)	15.15.11
7004	Blue Duffle	Packed	(0,0)	11.58.17
7004	Blue Duffle	Packed	(0,15)	12.8.32
7004	Blue Duffle	Repacked	(0,0)	15.24.50
7004	Blue Duffle	Repacked	(0,15)	15.36.26
7005	WtrPrf Backpack	Packed	(0,0)	12.37.20
7005	WtrPrf Backpack	Packed	(0,15)	12.44.12
7005	WtrPrf Backpack	Repacked	(0,0)	15.46.41
7005	WtrPrf Backpack	Repacked	(0,15)	15.56.14
7006	Large Black roller	Packed	(0,0)	13.38.53

7006	Large Black roller	Packed	upside-down	13.44.57
7006	Large Black roller	Repacked	(0,0)	16.3.47
7006	Large Black roller	Repacked	Upside-down	16.12.15
7007	Laptop case	Packed	(0,0)	14.1.33
7007	Laptop case	Packed	(0,15)	14.7.58
7007	Laptop case	re-packed	(0,90)	16.24.48
7007	Laptop case	re-packed	(0,0)	16.33.30

Distribution of Images from 1/6/2011

Training Datasets

7001	RedHardShell	Packed	(0,0)	10.34.46
7001	RedHardShell	RePacked	(0,15)	14.30.20
7002	Backpack	Packed	(0,0)	11.11.25
7002	Backpack	Repacked	(0,15)	14.58.5
7003	MedBlack Roller	Packed	(0,0)	11.31.19
7003	MedBlack Roller	Repacked	(0,15)	15.15.11
7004	Blue Duffle	Packed	(0,0)	11.58.17
7004	Blue Duffle	Repacked	(0,15)	15.36.26
7005	WtrPrf Backpack	Packed	(0,0)	12.37.20
7005	WtrPrf Backpack	Repacked	(0,15)	15.56.14
7006	Large Black roller	Packed	(0,0)	13.38.53
7006	Large Black roller	Repacked	Upside-down	16.12.15

Validation Datasets

7001	RedHardShell	Repacked	(0,0)	14.21.52
7002	Backpack	Packed	(0,15)	11.19.3
7003	Small Black Roller	Repacked	(0,0)	15.3.7
7004	Blue Duffle	Packed	(0,15)	12.8.32
7005	WtrPrf Backpack	Repacked	(0,0)	15.46.41
7006	Large Black roller	Packed	upside-down	13.44.57

Evaluation Datasets

7001	RedHardShell	Repacked	(0,15)	10.55.57
7002	Backpack	Repacked	(0,0)	14.52.23
7003	Small Black Roller	Packed	(0,15)	11.50.30
7004	Blue Duffle	Repacked	(0,0)	15.24.50
7005	WtrPrf Backpack	Packed	(0,15)	12.44.12
7006	Large Black roller	Repacked	(0,0)	16.3.47

On February 3, 2011, Alyssa collected 18 Datasets at the vendor. She used 6 bags to obtain these sets, bag numbers 7001-7006. There were 10-29 objects in each bag. All 24 geometric objects were spread out among these bags. Seventeen of the 17 sets have been segmented and sent to our participants. Eight were included in the Training set, 5 in the Validation set, and 4 in the evaluation set. One dataset was missing slices, and therefore not used.

Images Acquired on 2/3/2011

Bag #	Desc	Condition	Orientation	CT file
7001	RedHardShell	Packed	(0,0)	10.19.6

7001	RedHardShell	Shaken	(0,0)	10.26.30
7001	RedHardShell	Re-Packed	(0,0)	12.31.49
7002	Backpack	Packed	(0,0)	10.34.7
7002	Backpack	Shaken	(0,0)	10.43.2
7002	Backpack	Re-packed	(0,0)	12.44.30
7003	MedBlkRoller	Packed	(0,0)	10.49.3
7003	MedBlkRoller	Shaken	(0,0)	11.1.47
7003	MedBlkRoller	Re-Packed	(0,0)	12.51.55
7004	BlueDuffle	Packed	(0,0)	11.17.12
7004	BlueDuffle	Shaken	(0,0)	11.25.25
7004	BlueDuffle	Re-Packed	(0,0)	13.1.37
7005	WtrPrfBackpack	Packed	(0,0)	11.32.47
7005	wtrPrfBackpack	Shaken	(0,0)	11.39.30
7005	WtrPrfBackpack	Re-Packed	(0,0)	13.7.46
7006	LrgBlkRoller	Packed	(0,0)	11.57.34
7006	LrgBlkRoller	Shaken	(0,0)	12.20.19
7006	LrgBlkRoller	Re-Packed	(0,0)	13.16.43

Distribution of Images from 2/3/2011

Training set

7001	RedHardShell	Re-Packed	(0,0)	12.31.49
7002	Backpack	Packed	(0,0)	10.34.7
7002	Backpack	Re-packed	(0,0)	12.44.30
7003	MedBlkRoller	Shaken	(0,0)	11.1.47
7004	BlueDuffle	Shaken	(0,0)	11.25.25
7004	BlueDuffle	Re-Packed	(0,0)	13.1.37
7005	WtrPrfBackpack	Packed	(0,0)	11.32.47
7006	LrgBlkRoller	Shaken	(0,0)	12.20.19

Validation Set

7001	RedHardShell	Shaken	(0,0)	10.26.30
7002	Backpack	Shaken	(0,0)	10.43.2
7003	MedBlkRoller	Packed	(0,0)	10.49.3
7005	wtrPrfBackpack	Shaken	(0,0)	11.39.30
7006	LrgBlkRoller	Packed	(0,0)	11.57.34

Evaluation Set

7001	RedHardShell	Packed	(0,0)	10.19.6
7003	MedBlkRoller	Re-Packed	(0,0)	12.51.55
7004	BlueDuffle	Packed	(0,0)	11.17.12
7005	WtrPrfBackpack	Re-Packed	(0,0)	13.7.46

On March 15, 2011, Alyssa collected 18 Datasets at the vendor. She used 7 bags to collect these sets, bag numbers 7001 - 7006, and 7008. There were 10-17 objects in each bag. All 24 geometric objects were initially spread out between the 7 bags. Two bags, 7001 and 7008, were then re-packed with only geometric objects and clothing and re-imaged. Ten of the 24 geometric objects were contained in the re-packs of these bags. All 18 datasets were segmented and distributed to our participants. 10 were included in the Training set, 4 in the Validation set, and 4 in the Evaluation set.

Images Acquired on 3/15/2011

7001	RedHardShell	Packed	(0,0)	8.47.45
7001	RedHardShell	Packed	(0,15)	8.53.11
7001	RedHardShell	re-Packed	(0,0)	12.34.27
7001	RedHardShell	re-Packed	(0,15)	12.44.16
7002	Backpack	Packed	(0,0)	9.1.36
7002	Backpack	Packed	(0,15)	9.9.13
7003	MedBlkRoller	Packed	(0,0)	10.18.7
7003	MedBlkRoller	Packed	upside-down	10.27.4
7004	Blue Duffle	Packed	(0,0)	9.49.23
7004	Blue Duffle	Packed	(0,15)	10.7.19
7005	WtrPrfBackpack	Packed	(0,0)	9.19.38
7005	WtrPrfBackpack	Packed	(0,15)	9.31.4
7006	LrgBlkRoller	Packed	(0,0)	11.18.1
7006	LrgBlkRoller	Packed	upside-down	11.11.10
7008	Cardboard Box	Packed	(0,0)	11.27.55
7008	Cardboard Box	Packed	(0,10)	11.37.7
7008	Cardboard Box	re-packed	(0,0)	12.53.8
7008	Cardboard Box	re-packed	(0,10)	13.0.10

Distribution of Images from 3/15/2011

Training Set

7001	RedHardShell	Packed	(0,0)	8.47.45
7001	RedHardShell	re-Packed	(0,15)	12.44.16
7002	Backpack	Packed	(0,0)	9.1.36
7003	MedBlkRoller	Packed	upside-down	10.27.4
7004	Blue Duffle	Packed	(0,15)	10.7.19
7005	WtrPrfBackpack	Packed	(0,0)	9.19.38
7006	LrgBlkRoller	Packed	(0,0)	11.18.1
7008	Cardboard Box	Packed	(0,0)	11.27.55
7008	Cardboard Box	re-packed	(0,0)	12.53.8
7004	Blue Duffle	Packed	(0,0)	9.49.23

Validation Set

7001	RedHardShell	Packed	(0,15)	8.53.11
7002	Backpack	Packed	(0,15)	9.9.13
7008	Cardboard Box	Packed	(0,10)	11.37.7
7006	LrgBlkRoller	Packed	upside-down	11.11.10

Evaluation Set

7001	RedHardShell	re-Packed	(0,0)	12.34.27
7003	MedBlkRoller	Packed	(0,0)	10.18.7
7005	WtrPrfBackpack	Packed	(0,15)	9.31.4
7008	Cardboard Box	Packed	(0,10)	11.37.7

To provide an understanding of how the bags and objects are packed, a couple of packing lists (with associated CT images showing placement) are shown. Filler objects are denoted by "x"

Example List 1			
2	Clothes Iron	69	Rubber Sealant
5	Metal Frame	2011	Jewelry - Bracelets
14	Toy - Robot	2080	Radio
21	Aerosol - Metallic Paint	2097	Electrical Tape
31	Socks	3002	Digital Camera
66	Shampoo	3006	Hard Drive
67	Conditioner	4003	Rubbing Alcohol
		X	Sweater

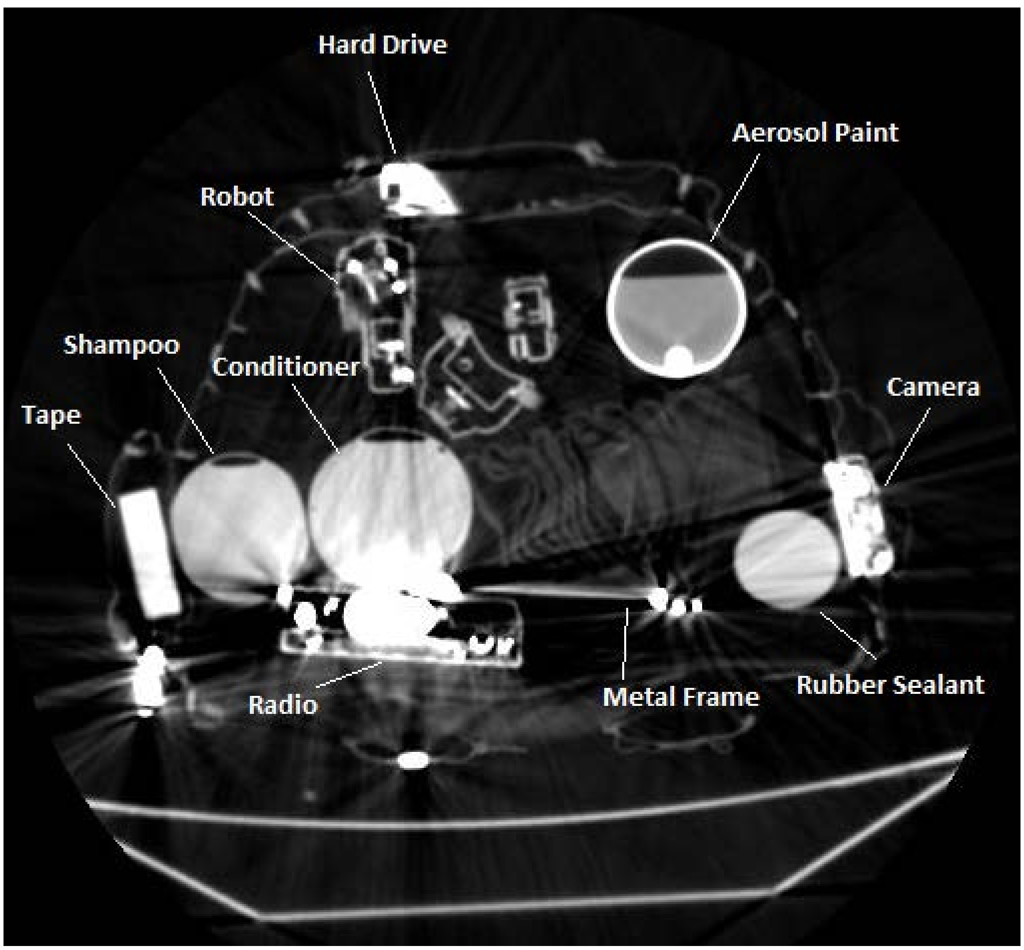


Figure 2: Packing list and CT Images for corresponding dataset. Note: CT images shown were acquired using a Medical CT scanner, not a commercial luggage scanner.

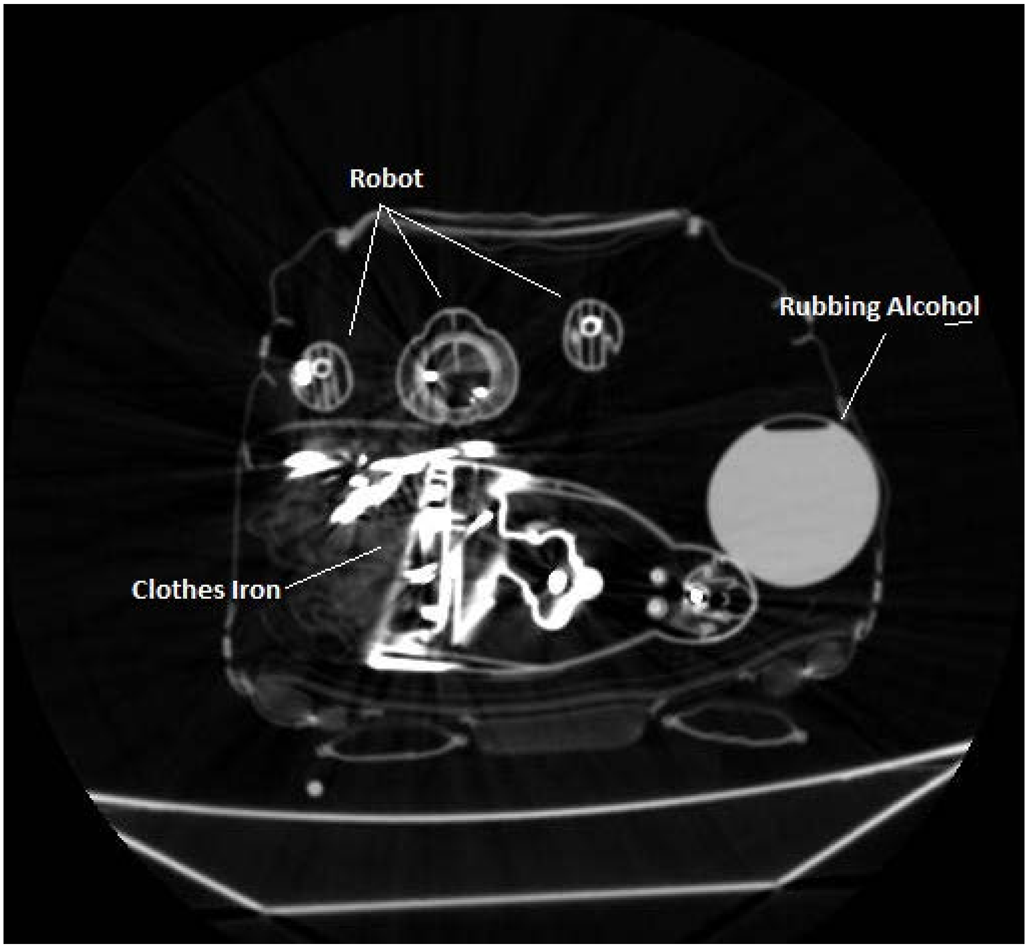


Figure 2: Continued

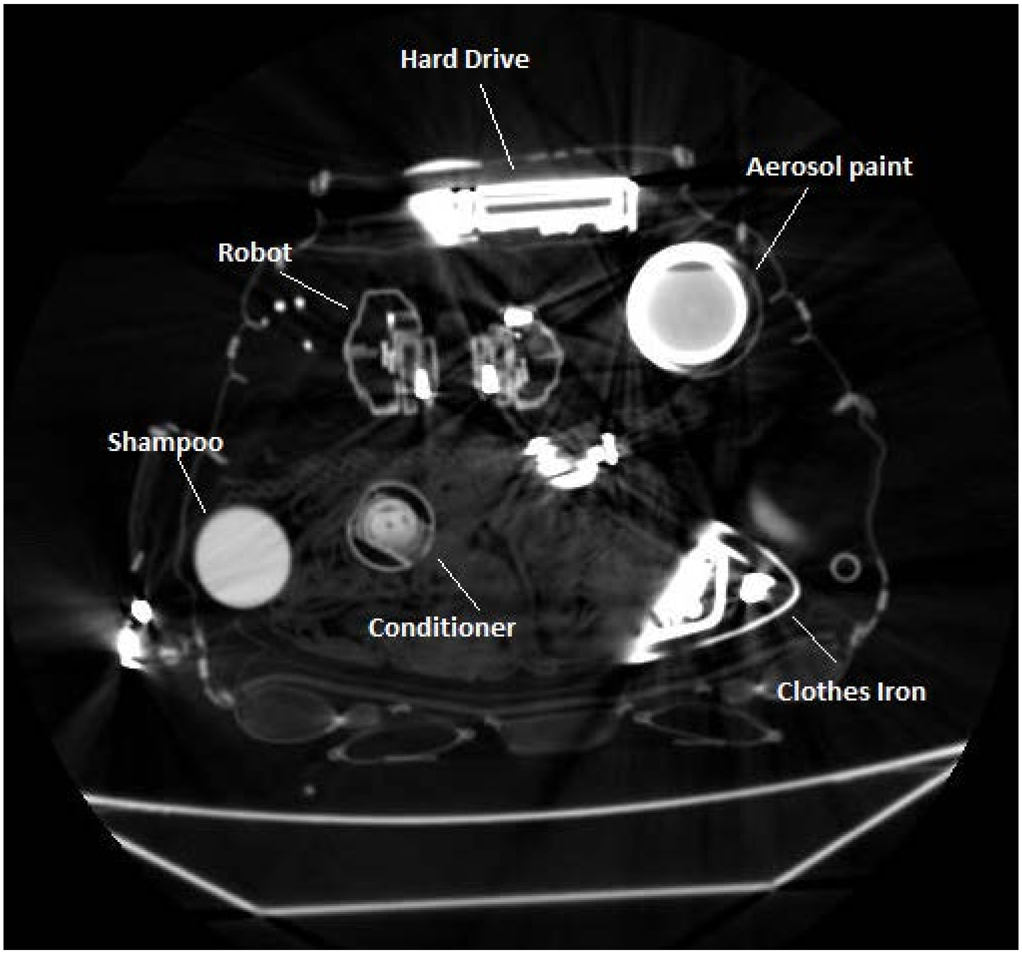


Figure 2: Continued

Example List 2			
17	Pot With Lid	2083	Tupperware - 3 Pk
21	Aerosol -Metallic Paint	2090	Butyl Rubber
30	Socks	2093	Neoprene (Thick)
50	Yoga Mat	4004	Acetone
51	2Liter Soda	4006	Motor Oil -2
56	8pk Soda	4055	Ac Adapter - Grey
61	Petroleum Jelly	4056	4pk Scotch Tape
63	Tealite Candles	4057	Laptop
64	Candle-Glass	8015	Large Nylon
1003	Flashlight-Large	8020	Butyl Rubber (Mid)
2004	Water Bottle	X	Sweatpants-Rolled
2008	Gel Pad	X	Shirt
2011	Jewelry-Bracelets	X	Sweater
2051	Honey	X	Sweater
2081	Small Electronic	X	Cami

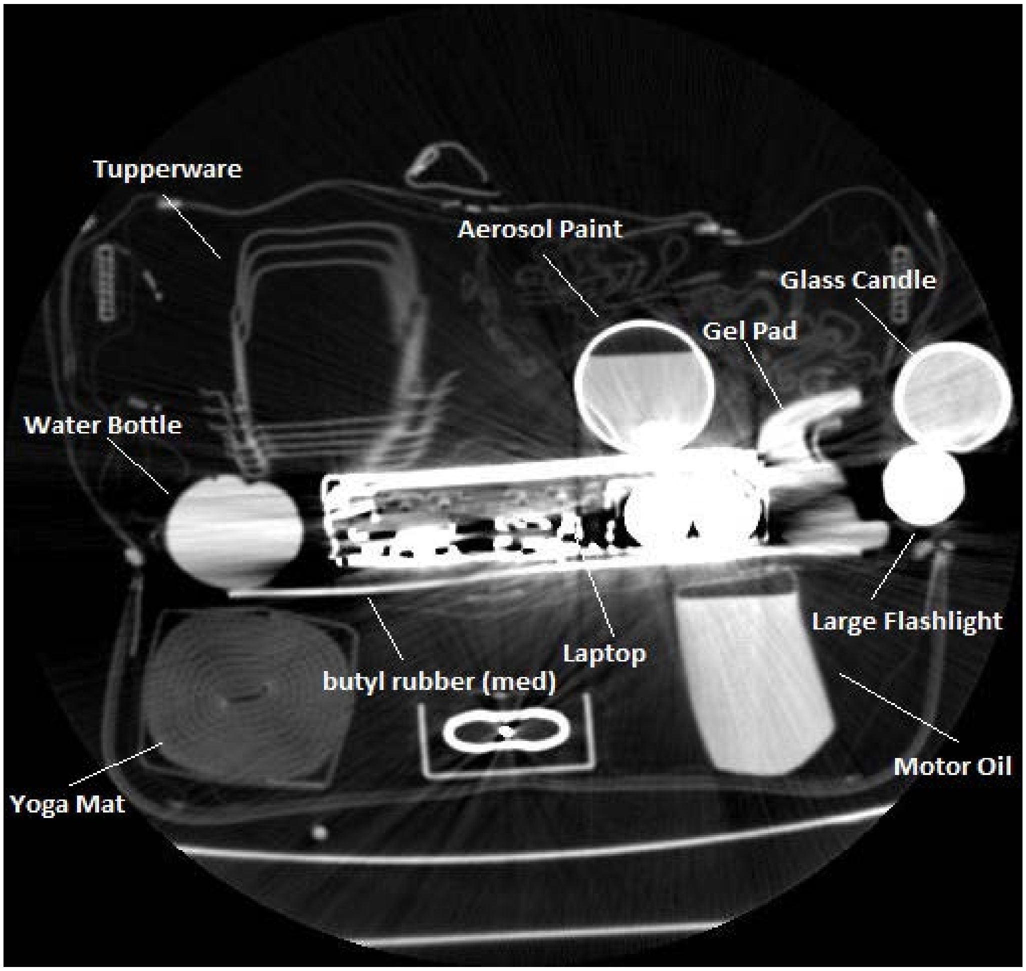


Figure 3: Packing list and CT image for corresponding dataset. Note: CT images shown were acquired using a Medical CT scanner, not a commercial luggage scanner.
Segmentation difficulty = 3

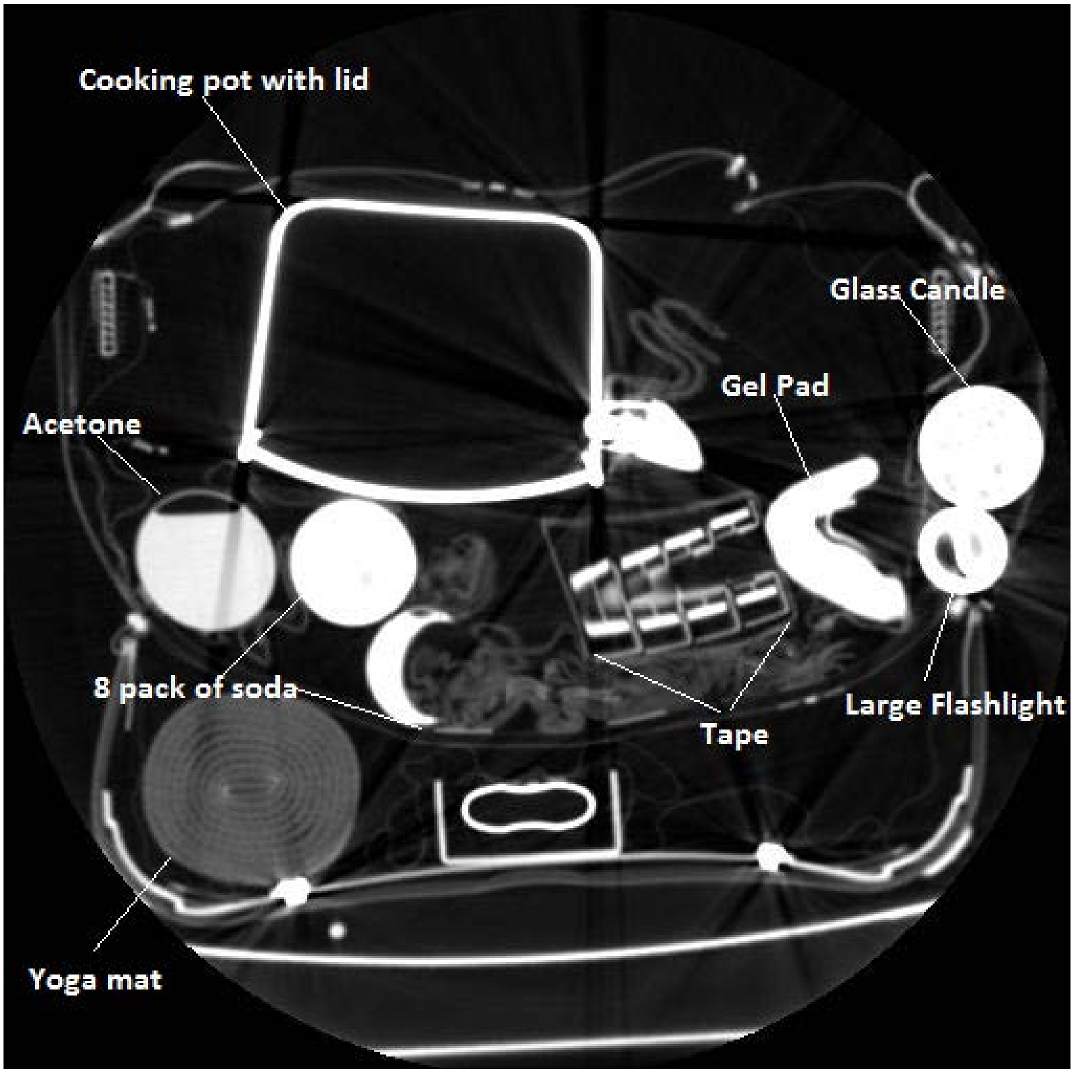


Figure 3: Continued

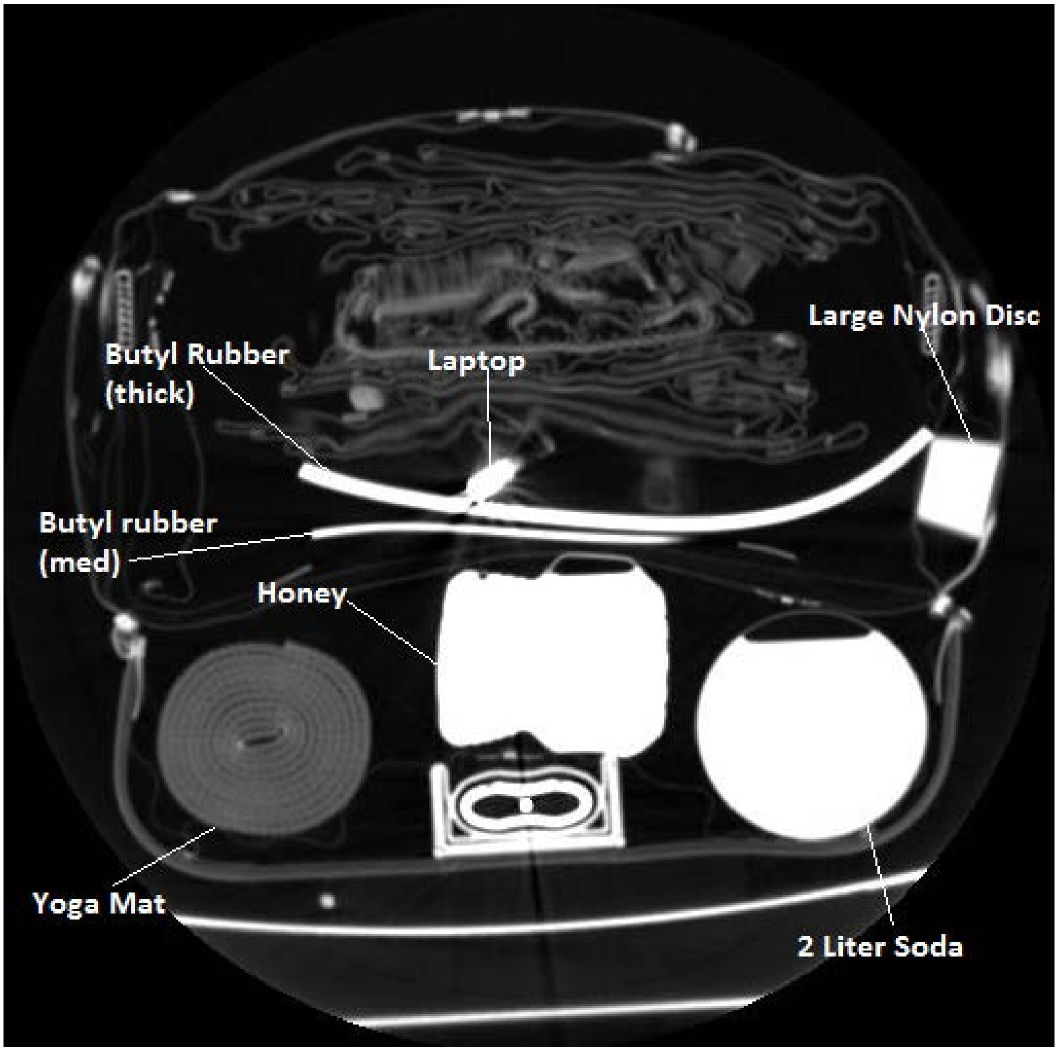


Figure 3: Continued

Reference segmentation maps were created for each dataset of packed luggage using the segmentation criteria of >500 Modified Hounsfield units (mHU) and ≥50mL. The segmentation maps were created using an ALERT manual or semi-automated segmentation algorithm running on MeVislab, a publicly available image processing software.

The Qualification and Training Dataset Groups were provided with information about the baggage, contents and reference segmentation map. The Validation Dataset Group will be provided to Researchers without the reference segmentation map. The Evaluation Dataset Group was reserved for use by the Domain Experts for evaluation purposes.

CT Segmentation Project Luggage Segmentation Process

Throughout the process of segmentation of luggage, we have observed a few main factors that greatly contribute to the difficulty of the task. These main factors include **artifacts** from metal objects, **thinness** of objects, and a number of issues that are caused by the **shape** of the object. Also the issue of **adjacent** objects is a main factor.

We used about 140 objects to pack the suitcases used for these datasets. They include clothing, jewelry, electronics, food, liquids, lotions and soaps, games, toys, books, and objects of interest that we strategically placed throughout the bags. The Objects of Interest, or OIs, include sheets of various thicknesses of Neoprene and Butyl rubber, as well as cylinders of Nylon, PVC, urethane foam, clay and aluminum. We tried different ways to mask or hide the sheet rubber OIs.

The method we used to segment objects involved two steps; manually placing an envelope around the OI, and thresholding the OI apart from anything else that may be contained within that envelope. The task of drawing this envelope has proven to be as difficult as expected. The main factors that cause difficulty in this area are: **thinness** of the object, **shape** and **changing of shape** between slices, and the human factor involved. It took the segmentor anywhere from 1-4 hours to segment a dataset, depending on the complexity, using this semi-automatic method.

The image is opened in a viewer that allows for semi-automatic or manual contouring of an object. The user may either allow the contour to attach itself automatically to changes in intensity gradients, or draw the contour freehanded. The number of slices needed to do this depends on how many slices the object is present in, and how much the shape of the object changes between slices. If the shape of the object, and thus the shape of the contour, changes greatly from slice to slice, the individual performing contouring will need to produce a lot more slices that have the object enveloped. There is an interpolation step which joins together all of the contours in order to envelope the entire object of interest in every slice it is present in. In order for this step to produce an accurate result, there must be good guidelines to follow.

The figure below is a screenshot of the network used for segmentation of objects. The orange colored modules are viewers used to show your image produced at each stage in the process. The green modules are not usually used directly by the person performing the segmentation, they are on the sidelines, processing data that is fed through. The blue modules, generally, are the interactive modules used by the segmentor to perform actions.

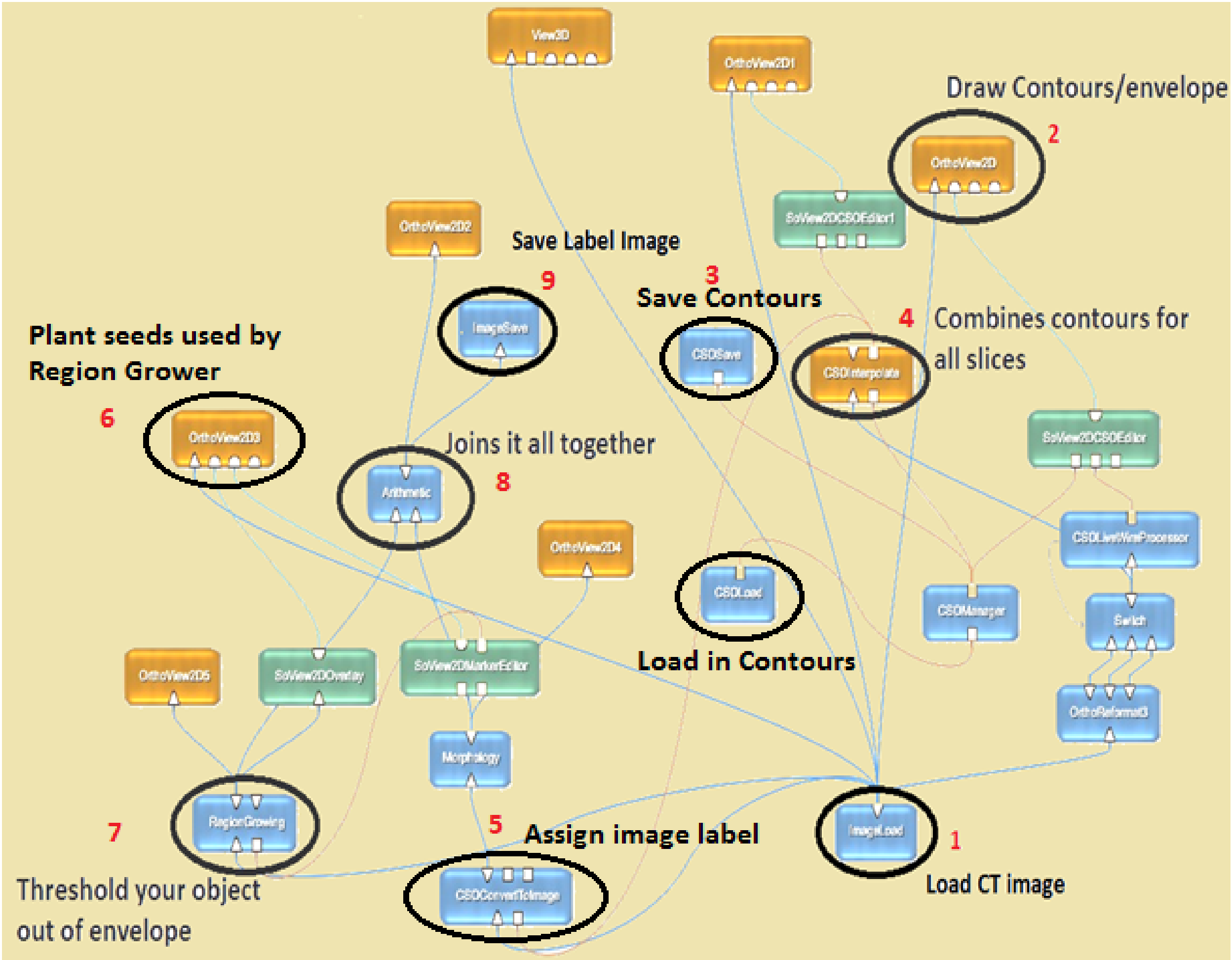
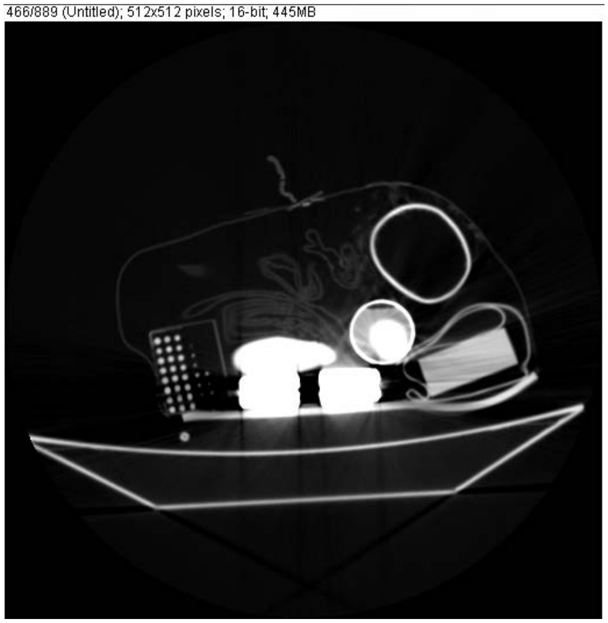


Figure 11: Screen shot of the network used to segment objects from a CT dataset. 1.) Start by Loading the CT image into the program. 2.) draw contours around the object of interest in multiple slices. 3.) Save contours in case the interpolation step is not successful and the program crashes. Once saved, contours can be loaded back in via CSOload module. 4.) Interpolation step combines these contours to produce an area of interest in every slice between the first and last slice selected. 5.) Converts all voxels within interpolated envelope to one label number, all voxels outside envelope are zero. 6.) Viewer shows original CT image. Segmentor plants seeds within the object to be segmented. 7.) Region growing allows application of thresholds. Beginning at voxels where seeds were planted, all voxels in contact that have a mHU value within specified thresholds will be considered 'object'. 8.) Arithmetic joins result of step 5 with result of step 7 together to produce one labeled object. 9.) Save the label image and move onto the next object in the dataset.

If the dataset being segmented contained 12 objects in the bag, this segmentation process would need to be repeated 12 times, once for each object. The product is 12 TIFF image files. We had to create a network for Mevislab that would join these 12 images together to produce the reference segmentation map. We call the reference segmentation map file the 'Aggregate Object file' or A.O. file. The network used to make these A.O. files is the Aggregator network.



CT Image (Training Dataset 15 slice 466)

A.O. Image, same slice

There were several problems we faced through the duration of this program that had to do with segmentation and the resulting A.O. files. These errors were found predominantly by the researchers within the Training and Validation data that was sent out by ALERT, as it was during these stages that the researchers were using the Aggregate Objet Reference Map images. ALERT created and dispersed multiple versions of the A.O. files as errors were found and corrected. It was discovered over the duration of the program that the main source of error was the inclusion of DICOM image headers into the Tiff image files that were created from the original DICOM CT data from the vendor. ALERT was unaware that these 8 byte headers were written into the CT TIFF image files. Another factor that contributed to the errors seen in the A.O. files was the nature of the software used to perform segmentation. MeVisLab proved to have an unordinary method of handling TIFF image files, which resulted in shifting of the segmentation images during the loading and saving process of the MeVisLab network.

The following is an excerpt from the document ‘info for researchers’ sent on September 6, 2011
“It was also brought to our attention by one of the researchers that the Aggregate Object files we provided were shifted in comparison to the CT data images. After initial inspection of this shift it was clear that the shift was not universal for the whole file, and could not be fixed by simply applying an offset to the data. It appeared that each individual object in the image was shifted by a different amount relative to the CT data. Upon further inspection it became clear that the MeVisLab image save module used by our segmentation and aggregation program was flawed. Our semi-automatic segmentation method involves a network on the program MeVislab, which allows us to segment and label one object at a time from the original CT data and save each object as its own individual file. We then take each individual file and add them into an aggregation network with the same program, using the same MeVisLab image save module. We save the developing A.O. file each time a new object is added in, until all objects have been added and there is a final save. By experimentation, we found that the MeVisLab

image save module shifts the data by 8 bytes every time it is used. Since each A.O file was saved a different number of times, depending on which order objects were added into the A.O. file, each object is shifted a different amount relative to its position on the original CT data image and the other objects in the A.O. file.

To compensate this error we remade all of the A.O. files for all 30 training data sets, by applying an 8 byte shift in the opposite direction each time we added in another object in order to compensate for the shift that happened the previous time it was saved. There is however one final save that must be done, so the whole A.O. image will be shifted 8 bytes to the right compared to the original CT data image."

We now know the reason for this 8 byte shift applied to each dataset each time the MeVisLab ImageSave module was used. At the time, when we corrected this shift and sent the new files, we were still not aware that the DICOM header had gotten carried over to the TIFF image files. We knew a shift was resulting but we were unclear about the source. We were simply trying to supply the researchers with more accurate A.O. reference map images. At the present time, the files have been fixed properly and there is no shifting of the images.

The following is another excerpt from the same document:

"Another issue that has been brought to our attention is that the TIFF files resulting from MeVislab are not readable by Matlab; however they are readable using ImageJ, and of course, MeVislab. The explanation is as follows: Mevislab saved the TIFF files as a non-standard 3D file structure. In general, 3D images are saved as multi-page TIFFs, i.e. multiple 2D images indexed and contained in one file. Apparently, MeVisLab saved the 3D image exactly as a 3D image with depth stored with a non-standard process. We think that the third dimension might be encoded in channels. ImageJ was able to read the TIFF without any problem; it issued an error but it was still able to load the data. On the other hand, Matlab's "imread" was not able to interpret MeVisLab's non-standard TIFF format. Our solution to this problem is to load the A.O. TIFF files into ImageJ, and save them as a TIFF that can be read by Matlab. We will send these files to any researchers who request them. "

The Subsequently, the same researcher group who reported these issues, also found that even with the adjustments made to the A.O. files, there remained small differences of 1-3 pixels in both the x and y direction when overlaying the A.O. files to the CT data. We evaluated this claim and also reproduced those differences. The errors were a result of the way that the segmenters had to load the CT Tiff image files into MeVisLab. The Mevislab ImageLoad module we used in the segmentation network could not simply load in Tiff files and align them correctly within the field of view. An offset had to be manually entered into the network in order to correctly center the image set. This offset was configured by the segmentor using a method that was reliant on visualization of the edges of the dataset field-of-view (FOV). It is for this reason that many of the A.O. files which resulted from segmentation of these datasets were shifted by 1-3 pixels in relation to the original CT DICOM data. ALERT determined that these small errors were within the acceptable % error which is expected from semi-automatic segmentation, and no action was taken to disperse new A.O. images to all of the researchers. Responsive to this data shift problem, Domain Expert Carl Crawford, wrote a code to correct all shifting errors in the A.O. image files. The new images output from his program had no shifting in relation to the

CT data from the Vendor, and since these files were not produced with Mevislab, they were able to be read in with Matlab software.

The following table highlights the data issues throughout the segmentation program

Question or problem	**Explanation**	**Solution**
Number of slices is different for DICOM and TIFF version of A.O. file for CT_15.28.8 in the Qualification set.	A.O. files (Aggregate Object files) are the ground truth files supplied to researchers from ALERT. The data comes to us from the Vendor in DICOM format. We must convert these DICOM files to Tif format ourselves. In Multiple datasets, we may have cut off slices at the end of the CT dataset in the Tiff files.	The slices at the end of the image that are cut off from the Tiff version do not contain any data, they are slices containing only air. Slice # 1 of the DICOM does directly correspond to slice #1 of the Tiff file, so this can be ignored.
Researcher reported that He could not see some of the label images in the A.O. files	Our label numbers for objects vary from 2-9999, so the objects with low label numbers may not appear in the image with normal contrast and baseline settings.	Adjusting these settings will allow objects with lower label numbers to be viewed.
The DICOM version of the CT data for one of the Training datasets was missing from the drives sent out to the researchers.	Training.Dataset7.CT_14.30.20 was missing a DICOM file	Distribute missing file out to all researchers
Objects in A.O. files seem to be shifted by varying amounts compared to position on CT data from vendor.	The Aggregator network used to make the A.O. files involved loading each individual segmented object file into the network, one by one, to produce a file containing all objects in that Dataset. The ImageSave module of that network applied an 8 byte offset to the data with each object that was saved. This resulted in each individual segmented object file being shifted by different amounts in the A.O. file compared to its original position.	Re-make all A.O. files with the aggregator network, compensating ahead of time for the 8 byte shift. This will produce an A.O. file that is shifted as a whole by 8 bytes in relation to the CT data, (rather than each object being shifted around by a different number of bytes). Send these new A.O. files to researchers, with instruction to shift the image by 8 bytes.

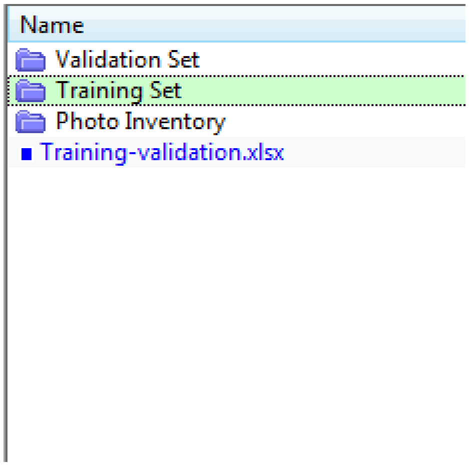
A.O. tiff files cannot be read into matlab	The Tiff files that are saved and output from MeVisLab are not compatible with Matlab.	Load the A.O. Tiff file that was saved in Mevislab into ImageJ, save as Tiff. This file will be compatible with Matlab.
A.O. files, when overlaid onto original CT data, do not line up perfectly. There is some amount of shift in the X and/or Y direction.	When loading the CT data Tiff file into MevisLab, an offset needs to be applied in order to center the image in the field of view. This offset was determined manually (visually). Some (about half) of these visually determined offsets were off by anywhere from 1-5 pixels in the X and/or Y direction. This results in the A.O. files that are made from this image to be shifted the same way. When these files are compared to the CT data, there is some offset.	Offset errors were found to be on the same order of magnitude that could be expected from semi-automatic segmentation, therefore will not greatly affect the researchers work.

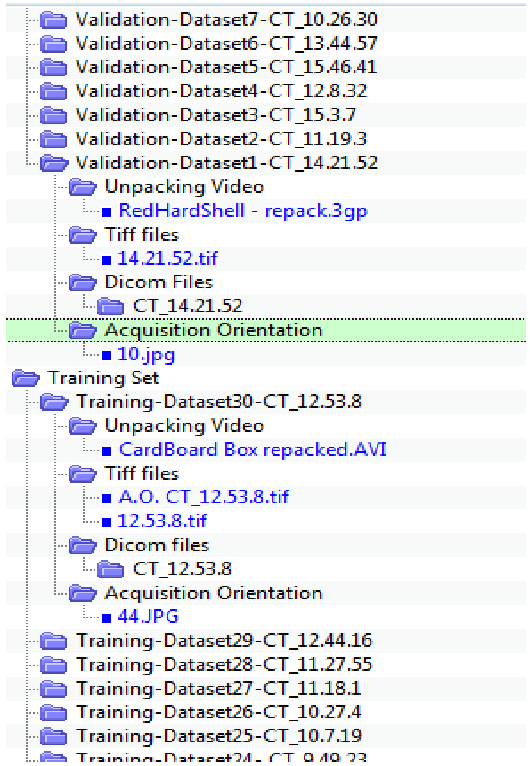
9.2.1.4 Distribution of Data

Between January and March of 2011, ALERT distributed the Qualification datasets to all researchers who submitted a proposal, and signed an NDA for the segmentation challenge. The data was sent to 12 researchers and the 3 Domain Experts.

In May, after the phase 2 proposals were reviewed, we sent Training and Validation data to the 5 participants chosen to go forward. We prepared 30 Training datasets, and 15 Validation datasets. The training datasets we provided were complete with the A.O. reference map files, while the validation sets did not include these files.

The following shows the file structure of the Training and Validation datasets as they were on the drive given to the researchers:





Main level Detailed

One of the researchers noticed that a DICOM file was missing from one of the training datasets, and we promptly sent the missing file out to all the researchers.

As previously discussed, there was an 8-byte shifting error in the A.O. files which was corrected and ALERT distributed new A.O. files for the Training data on July 19, 2011.

In September of 2011, wALERT distributed the 15 Validation A.O. files, along with the Evaluation data which did not include A.O. files on September 5, 2011.

The Evaluation A.O. files, and some individual object CT images for the OIs were sent to the Domain Experts only on September 16, 2011.

ALERT was made aware that there were still minor shifting errors of 1-3 voxels in 54% of the cases, between the A.O. images and the CT images. These shifts were in both the X and Y direction, and were corrected by an automatic program written by Carl Crawford. These new A.O. files that were run through his program do not have any shifting in relation to the CT data, and they are compatible with Matlab software. The files were distributed only to the research group that identified the error and requested the new files.

The table below details the distribution of ALERT segmentation data. All data distributed was encrypted using TrueCrypt at the media level.

Date - 2011	Name of data	Media Type	Description	Sent to
January - March	Qualification (Phase 1) Data	DVD	2 Datasets, complete with ground truth files	DEs and all researchers who submitted Proposal and signed NDA
May – June (Varies between researchers)	Training and Validation datasets	1TB USB external hard drive	30 Training datasets, complete with A.O., and 15 Validation datasets, not including A.O. files	5 chosen researchers and DEs
May 22	Training Dataset7 - DICOM file	DVD	DICOM version of Training Dataset 7 was missing from Hard drives	5 chosen researchers and DEs
July 19	New A.O. files for Training Datasets.	16GB flash drive	Error in module creating A.O. files, all 30 A.O. files for Training Dataset corrected and redistributed.	5 chosen researchers and DEs
September 5	Validation A.O. files and Evaluation CT Datasets	160GB USB external hard drive	A.O. files for 15 Validation Datasets, as well as 14 Evaluation datasets, without A.O. files	5 chosen researchers and DEs
September 16	Evaluation A.O. files and individual object scans for OOIs	16GB flash drive	14 A.O. files for Evaluation dataset, as well as individual object CT datasets for OOIs	Domain Experts Only
November 16	Final, corrected A.O. files for Training and Validation datasets	16GB flash drive	30 A.O. files for Training Set, 15 A.O. files for Validation Set	UEA only

9.2.1.5 Creation of Datasets

-Packing of bags
-scanning of bags
-photos/videos
- all documentation (spreadsheets)
-Splitting 4 dates of acquisitions into T.V and E.

Segmentation

- Process, software

- Lessons learned and problems

Dispersal of data

- When sent and to whom
- Re-sending data
- Documentation of all data
- Media and encryption

Archive data – prepared to send to Harry

9.2.2 Appendix: CT Segmentation – Lessons Learned," Alyssa White and Rick Moore

This document has been deemed SSI and as such will only be referenced here rather than included.