Towards In-baggage Suspicious Object Detection Using Commodity WiFi

Yingying (Jennifer) Chen

WINLAB
Department of Electrical and Computer Engineering
Rutgers University
New Brunswick, NJ 08854
Email: yingche@scarletmail.rutgers.edu
Web: http://www.winlab.rutgers.edu/~yychen/

October 17, 2018

IEEE CNS 2018 Best Paper
Interviewed by CBS TV, BBC News, NBC New York, IEEE Engineering 360

RUTGERS
UNIVERSITY | NEW BRUNSWICK

WINLAB

So What? Who Cares?

- **Space:** detecting suspicious objects in baggage (e.g., lethal weapons, home-made bombs and explosive chemicals)
- **Problem:** manual examination and expensive inspection equipment (e.g., X-ray machine in airport) are hard to be widely deployed
- **Solution:** exploiting WiFi signals to provide a low-cost and easy-to-scale solution; capturing the signal interferences to detect suspicious objects and further identify the dangerous level of the object
- **Results:**
  - Detecting suspicious object and identifying dangerous material type (e.g., metal and liquid)
  - Examining the object's dimension (i.e., metal object shape or liquid volume)
- **TRL:** 8
- **Contact me**
  - Email: yingche@scarletmail.rutgers.edu

Motivation

Boston Marathon Bombing 2013

Las Vegas Shooting 2017

Transparent Bags?

Need expensive CT and X-ray machines everywhere

We provide a low-cost solution leveraging the commodity WiFi device to detect suspicious hidden objects

Attack Model

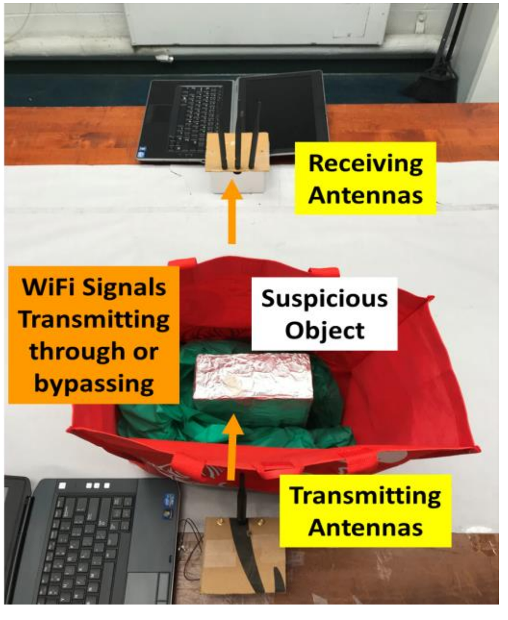
- An adversary intentionally or unintentionally carries dangerous items
  - Lethal weapons, home-made bombs and explosive chemicals
- In-baggage suspicious objects
  - Metal: guns, knives, laptops and batteries
  - Liquid: water, acid, alcohol and other chemicals
- Vulnerable areas
  - Schools, museums, stadiums, theme parks, Metro/train stations and scenic locations
  - No pre-installed security check infrastructures
  - High-manpower for security checks

Solution Overview

- Using a pair of commodity WiFi devices and deep learning-based signal selection
- Examining fine-grained Channel State Information (CSI) from WiFi signals
  - Amplitude and phase information of 30 subcarriers
- Capturing various interferences by the objects based on CSI
  - Absorption, refraction and reflection

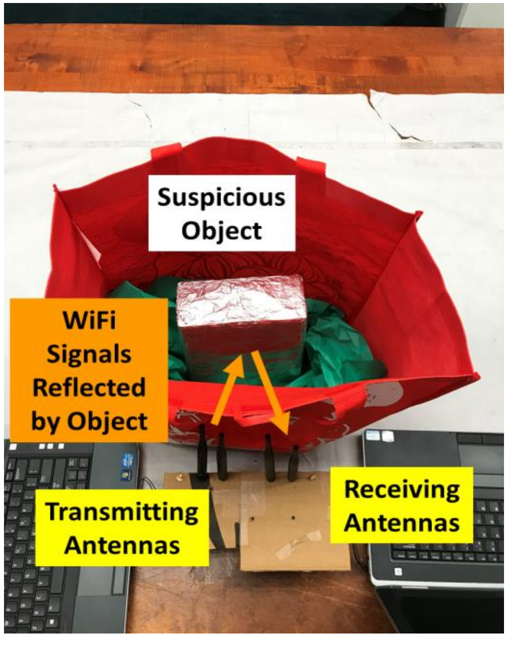
Identifying the object material based on signal absorption and refraction

Machine learning-based classifier



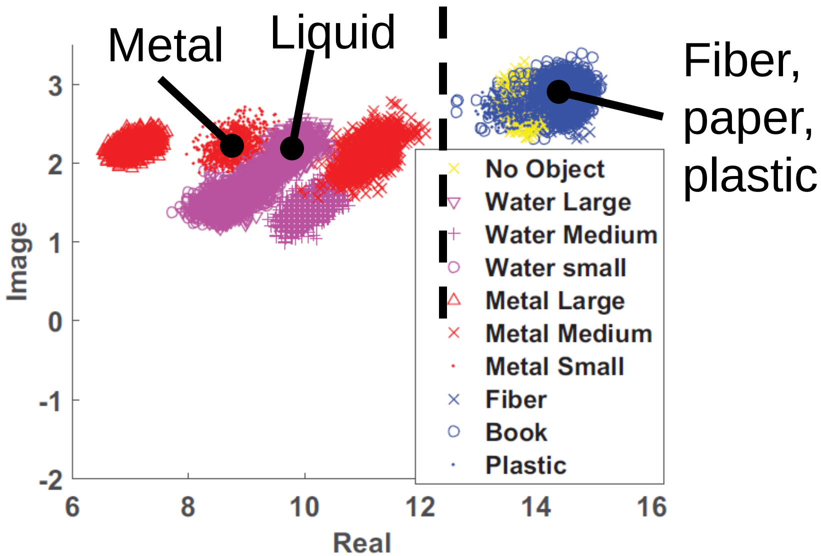
Estimating the object shape based on signal reflection

Neural network-based method

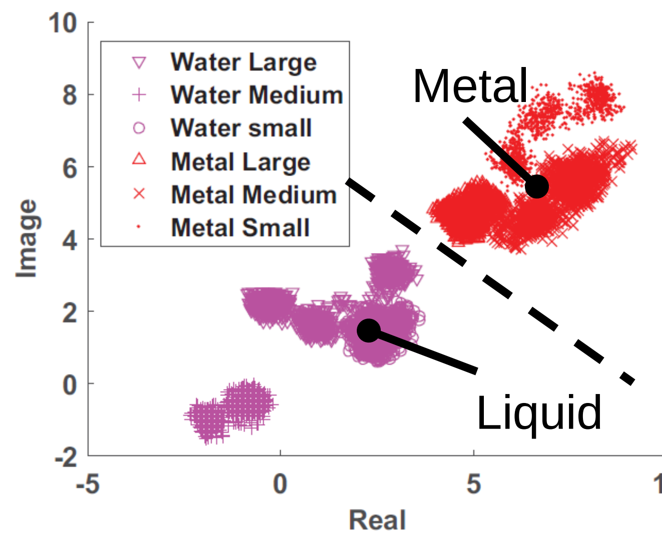


Machine Learning Based Material Classification Leveraging CSI

- ❑ Signal absorption and refraction are captured based on CSI
- ❑ Learning-based classifiers (e.g., SVM) are used
- ❑ Detecting suspicious object with 95% successful rate
- ❑ Identifying the material (e.g., metal or liquid) with 90% accuracy



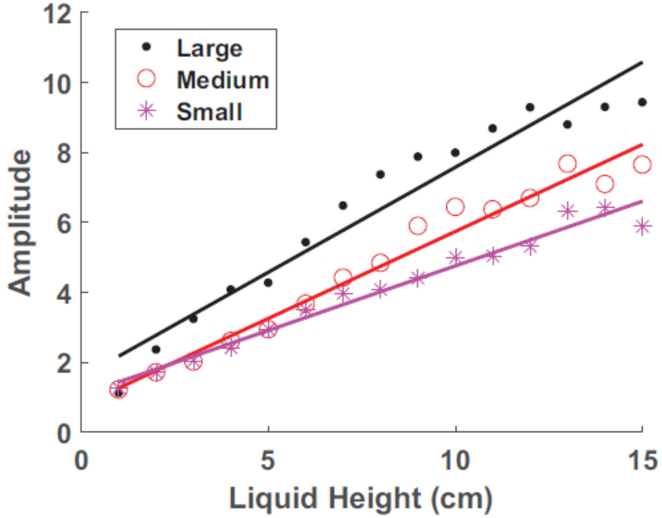
Step1: Differentiate dangerous and non-dangerous objects based on CSI complex values



Step2: Identify dangerous material (e.g., metal and liquid) based on CSI differences between antennas

Object Risk Estimation: Liquid Volume Estimation

- Signal reflection by objects is extracted from CSI
- Neural network-based method or linear regression model are developed to estimate the liquid volume



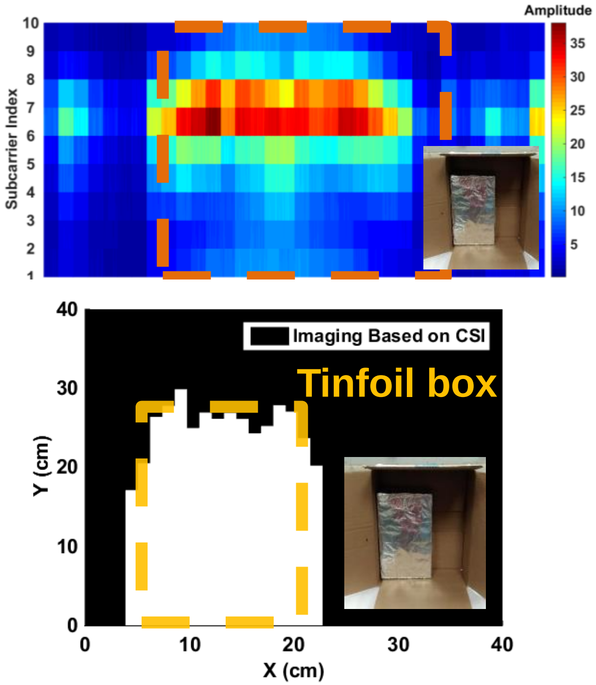
Deriving the relationship between CSI amplitude and liquid height per subcarrier

Liquid volume estimation with median error 16ml

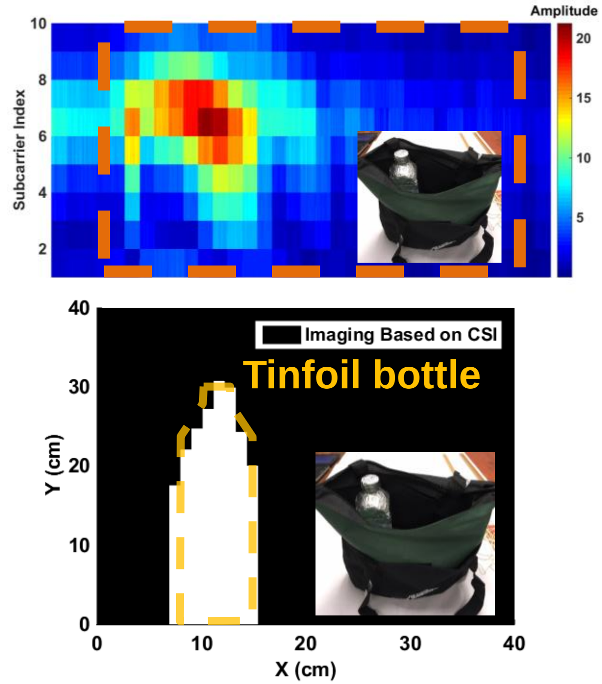
Object Risk Estimation: Metal Object Imaging

Signal reflection by the object is extracted from CSI for shape estimation

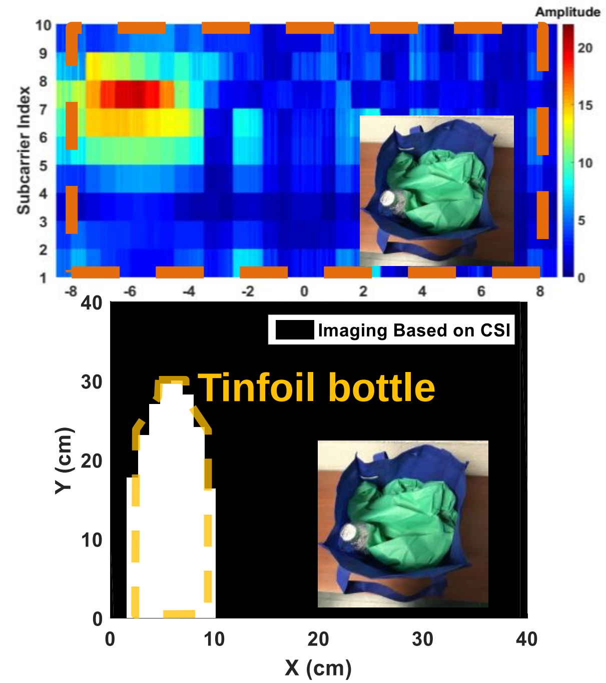
Tinfoil box in package box



Tinfoil bottle in handbag



Tinfoil bottle in tote bag with clothes



Average errors to estimate metal objects' width and height: 0.3cm and 0.5cm

RUTGERS
UNIVERSITY | NEW BRUNSWICK

WINLAB

What is Next?

- Limitations of current solution and how to mitigate?
  - Evaluating the system model with real dangerous objects (e.g., weapons)

Pistol Display model
https://bit.ly/2pTqSoW

  - Extensive system performance testing in public places (e.g., schools and train stations)
  - Developing hand-held WiFi devices (e.g., smartphone) or robot-based miniPC to support fully portable dangerous object detection
- How to address an adapting adversary?
  - Dynamically updating the system model with more and new dangerous objects

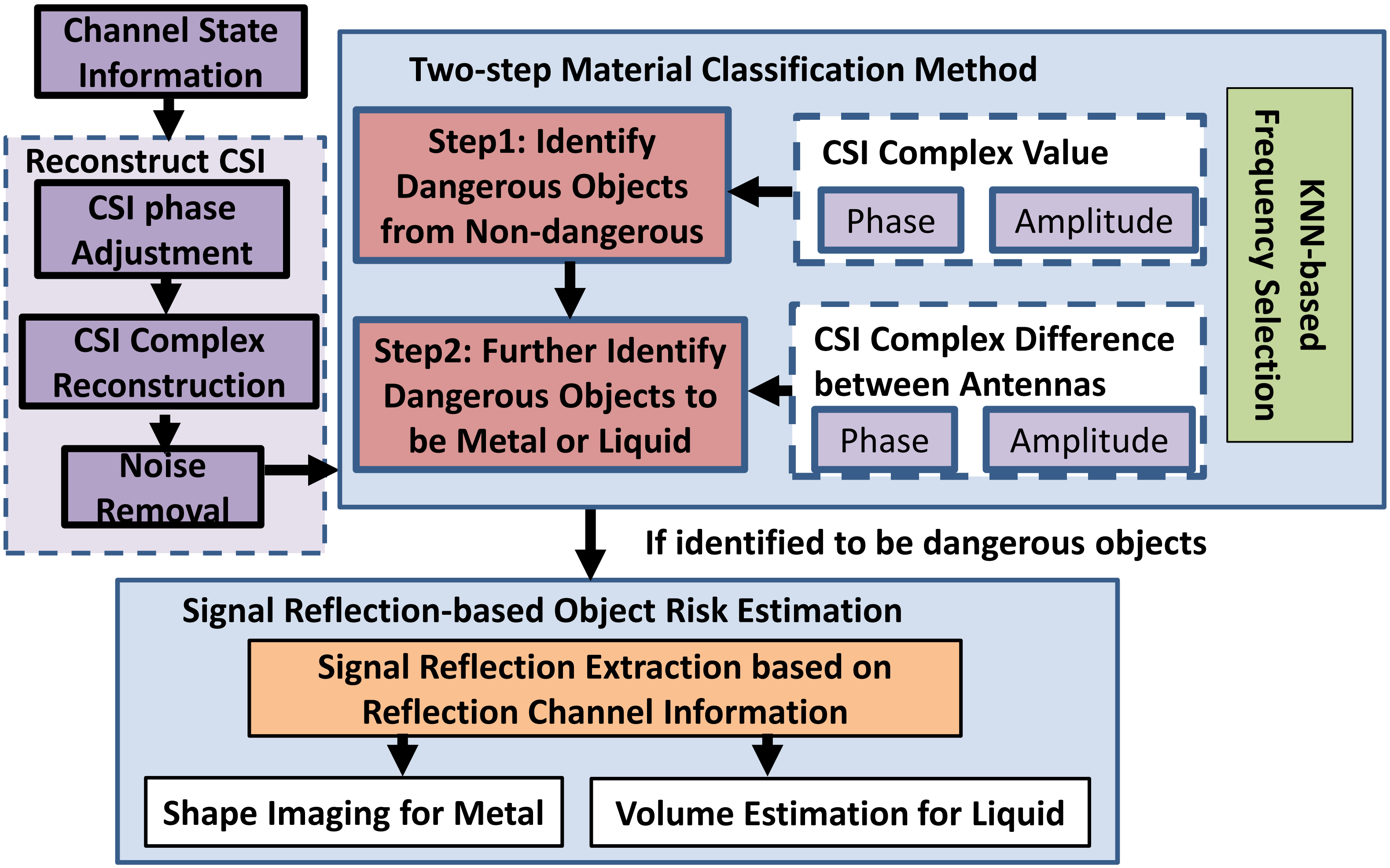
RUTGERS
UNIVERSITY | NEW BRUNSWICK

WINLAB

Backup: Related Work

- Traditional in-baggage suspicious object detection
  - Manual examination at checkpoints
  - Expensive dedicated equipment
    - CT volumetric imagery
    - X-ray machine
- Recent RF signal-based method
  - Specialized signal
    - 60 GHz radar, RFID, USRP
  - Large antenna arrays
  - Hard to differentiate both material and shape

Backup: System Flow

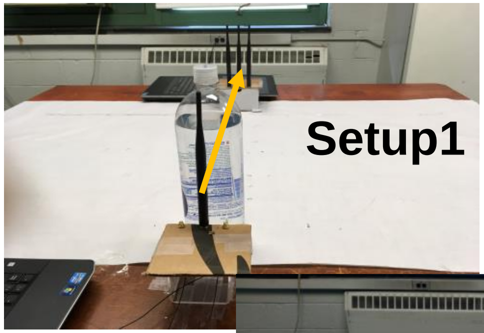


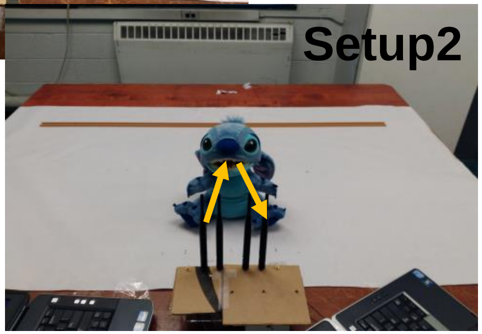
RUTGERS UNIVERSITY | NEW BRUNSWICK

WINLAB

Backup: Experimental Methodology

- **Experimental Setup**
  - Two Dell Latitude E6430 laptops
    - Ubuntu 10.04 LTS with the kernel 2.6.36
    - IWL 5300 wireless cards
    - Four 6dBi omnidirectional dual band rubber ducky antennas
  - Frequency band: 5GHz
  - Packet rate: 100pkt/sec
  - Typical indoor room with two people
- **Setup1:** Tx and Rx are placed apart for material classification
- **Setup2:** Tx and Rx are placed closely for imaging the object



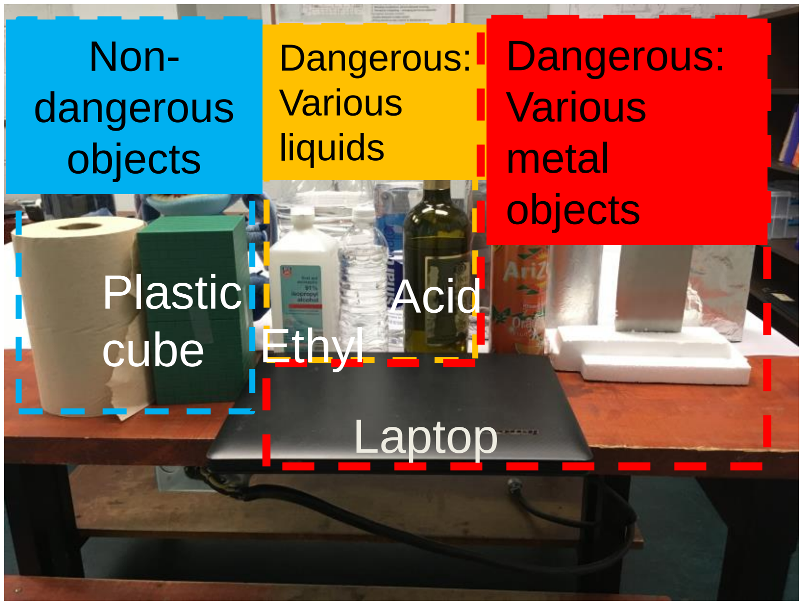


RUTGERS
UNIVERSITY | NEW BRUNSWICK

WINLAB

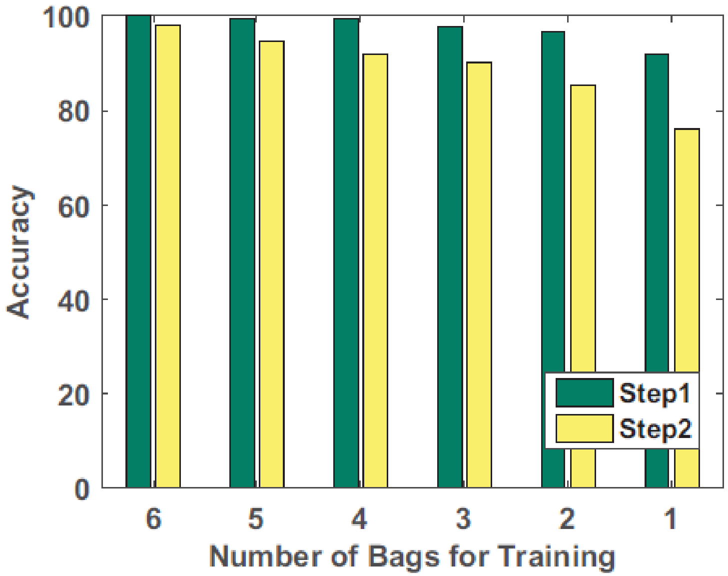
Backup: Experimental Methodology

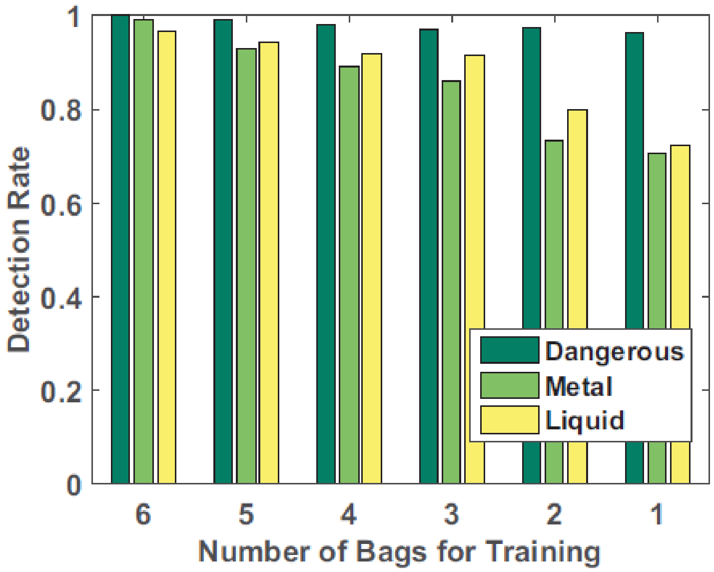
❑15 target objects



❑6 representative bags/boxes

Backup: Performance of Material Classification





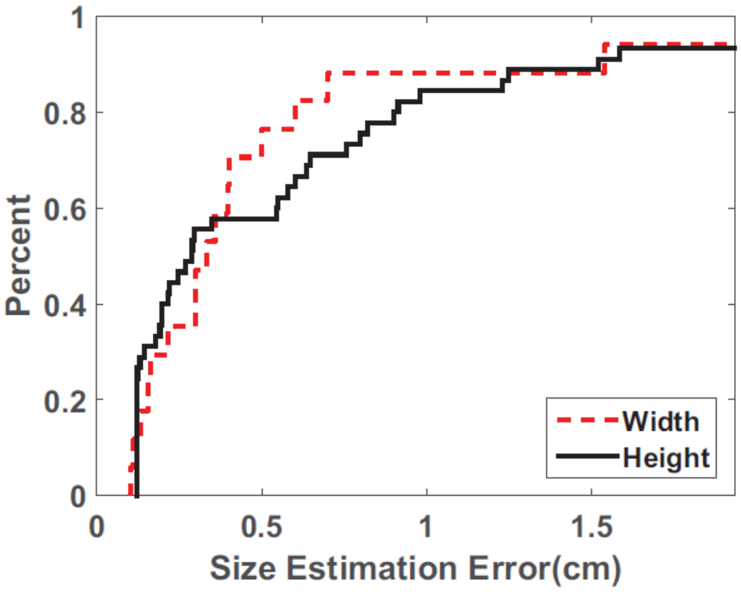
99% accuracy to classify dangerous and non-dangerous
97% accuracy to differentiate metal and liquid

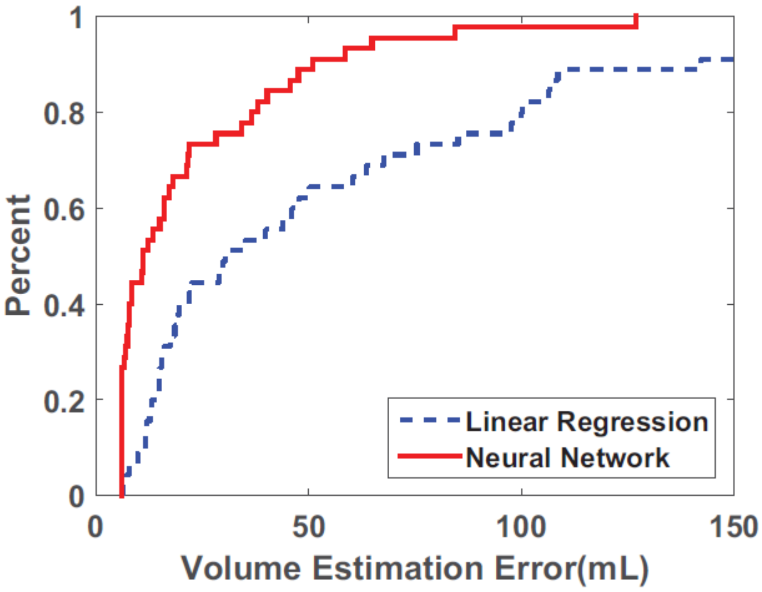
Detection rate for the dangerous material, metal and liquid are 99%, 98% and 95%.

RUTGERS
UNIVERSITY | NEW BRUNSWICK

WINLAB

Backup: Risk Level Estimation based on Object Imaging





Metal objects' width and height estimation average errors 0.3cm and 0.5cm

Liquid volume estimation with median error 16ml

RUTGERS
UNIVERSITY | NEW BRUNSWICK

WINLAB