



ARL

Small Drone Field Experiment: Data Collection & Processing

Dalton Rosario, Christoph Borel, Damon Conover

U.S Army Research Laboratory

Ryan McAlinden

University of Southern California Institute for Creative Technologies

Anthony Ortiz^a, Sarah Shiver^b, Blair Simon^c

^aUniversity of Texas – El Paso, ^bUniversity of California – Santa Barbara

^cHeadwall Photonics



Current and future ground operations rely on multi-sensing capabilities from UAS assets to provide enhanced persistent wide area coverage. Remote sensing from small UAS can map terrain features of potential conflict areas (e.g., urban areas) and classify & localize target materials to provide enhanced situational awareness



U.S. ARMY
RDECOM

Ground & Aerial USC Data Collection **ARL**

USC Data Supported ARL West Summer Projects



Drone: Phantom 3 quadcopter
Camera: GoPro 3
Gimbal: 3-axis stabilization
GPS/IMU



Drone: Leica Aibotix X6 hexa-rotor
Sensor: Headwall's Nano-Hyperspec
Gimbal: 3-axis stabilization
GPS/IMU

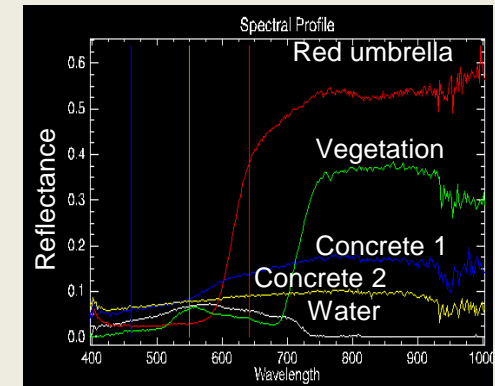


Objective

- Explore the value of COTS drone/sensor system emerging technologies for enhanced Image Understanding
- Develop capability based on **fusion of 3D DEMs & spectra** for scene segmentation, and adaptive machine learning
- **Jointly organize & conduct w/ ICT a data collection at USC main campus**, consisting of ground-based and drone-based hyperspectral remote sensing, and drone based sensing for 3D point clouds from photogrammetry

Impact

- Adaptive, Aerial Situational Awareness
 - Material classification map for Common Operating Picture (COP)
 - Adaptive semi-supervised machine learning



*ARL, ARL West
USC/ ICT
Headwall Photonics
Leica Geosystems*



U.S. ARMY
RDECOM

USC Data Post-processing



Ground Data Acquisition



SOC 700



Aerial Data Acquisition

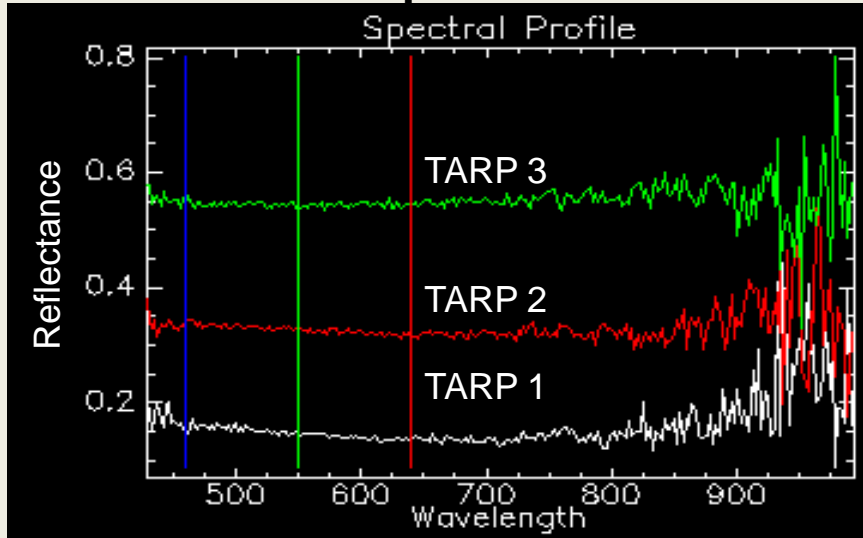
Headwall Nano-HyperSpec



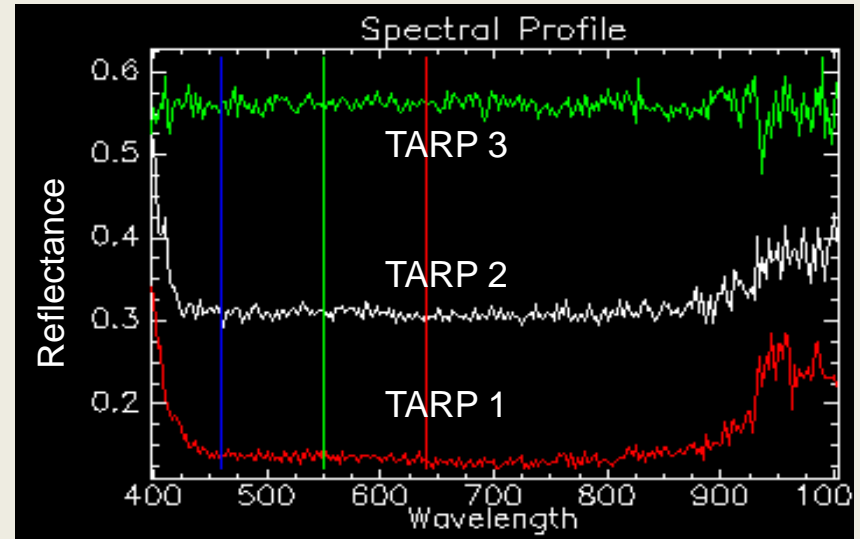
TARPS



SOC Ground Tarp Data



Headwall Aerial Tarp Data





U.S. ARMY
RDECOM

USC Data Post-processing



Google
Map



Low resolution Mosaic
(17000x13000x272) from RGB image
patches using all data cubes collected w/
Headwall Nano-hyperSpec sensor



U.S. ARMY
RDECOM

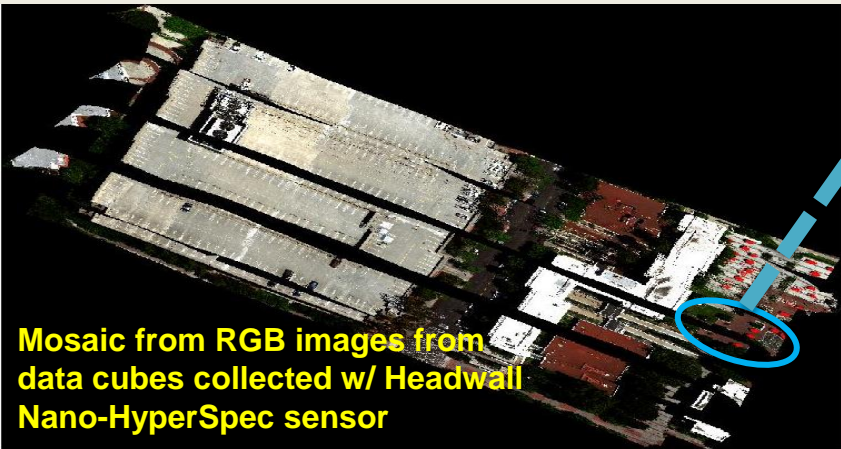
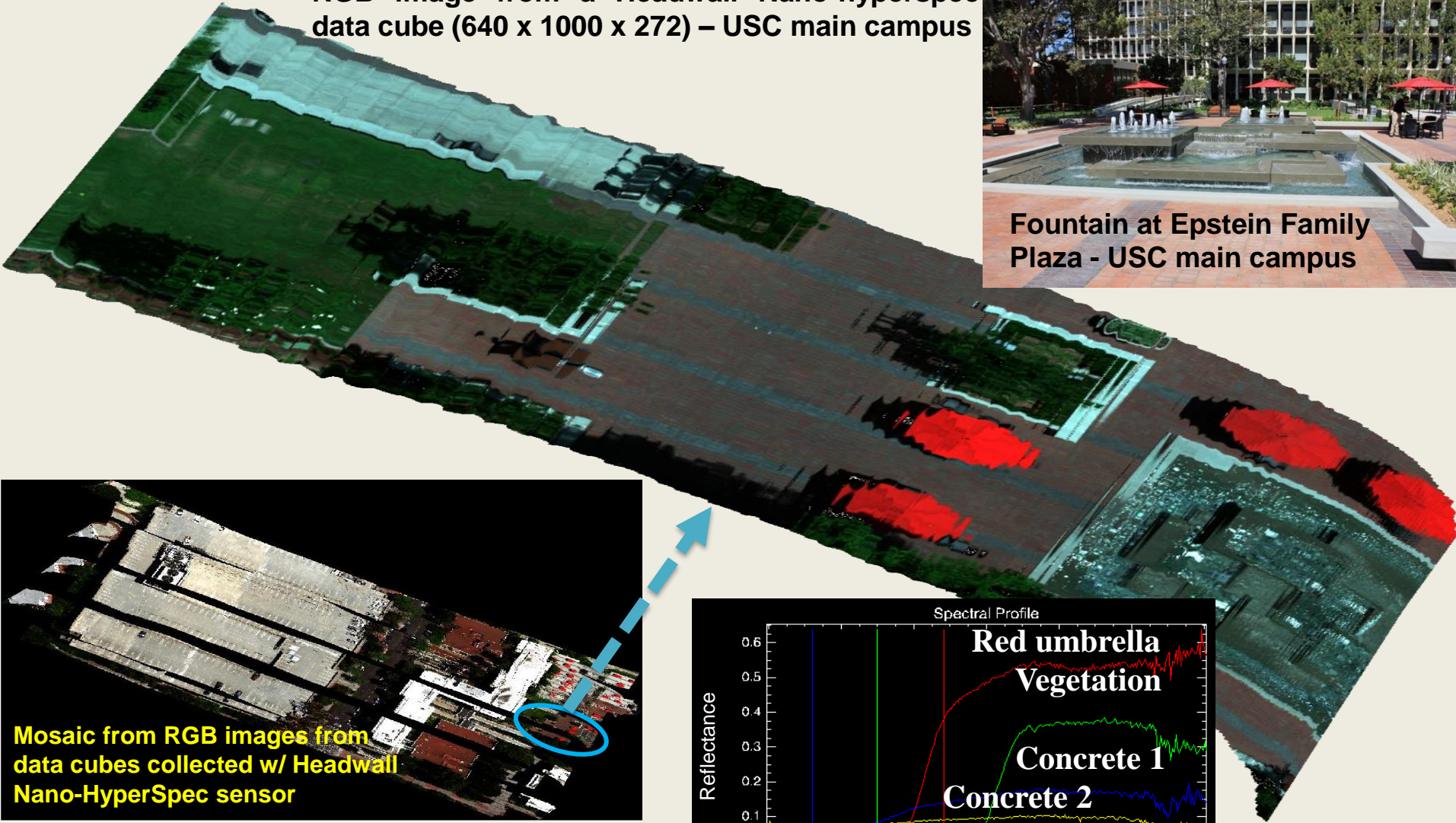
USC Data Post-processing



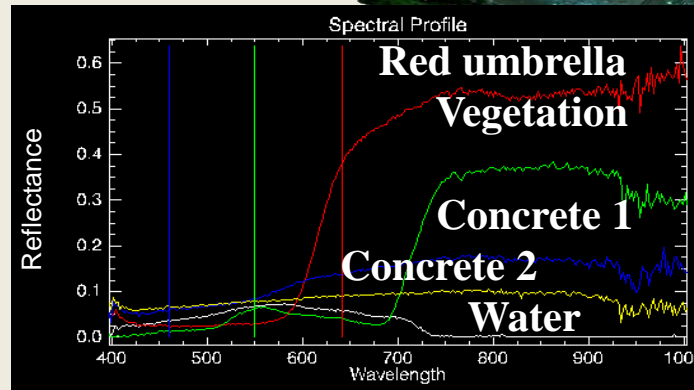
RGB image from a Headwall Nano-hyperspec data cube (640 x 1000 x 272) – USC main campus



Fountain at Epstein Family Plaza - USC main campus



Mosaic from RGB images from data cubes collected w/ Headwall Nano-HyperSpec sensor



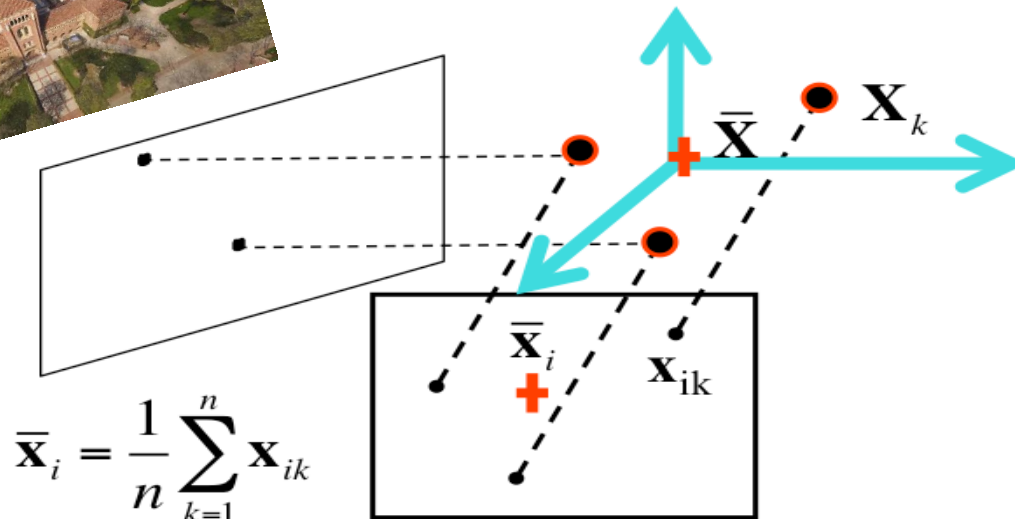


A factorization method - Centering the data

If the centroid of points in 3D = center of the world reference system



$$\hat{\mathbf{x}}_{ij} = \mathbf{A}_i \hat{\mathbf{X}}_j = \mathbf{A}_i \mathbf{X}_j$$



$$\bar{\mathbf{x}}_i = \frac{1}{n} \sum_{k=1}^n \mathbf{x}_{ik}$$

$$\bar{\mathbf{X}} = \frac{1}{n} \sum_{k=1}^n \mathbf{X}_k$$

Centroid of 3D points



Goal: given spatial features from a query image I , corresponding to 3D point structures, match equivalent spatial features from hyperspectral imagery

Equivalent to: from a collection of derived 3D point clouds, find corresponding landmarks in relevant images that fits invariant spatial features in hyperspectral imagery

Equivalent to a fitting problem!

- Generate hypothesis
- Verify hypothesis
- Select hypothesis with lowest fitting error
- Generate matching results

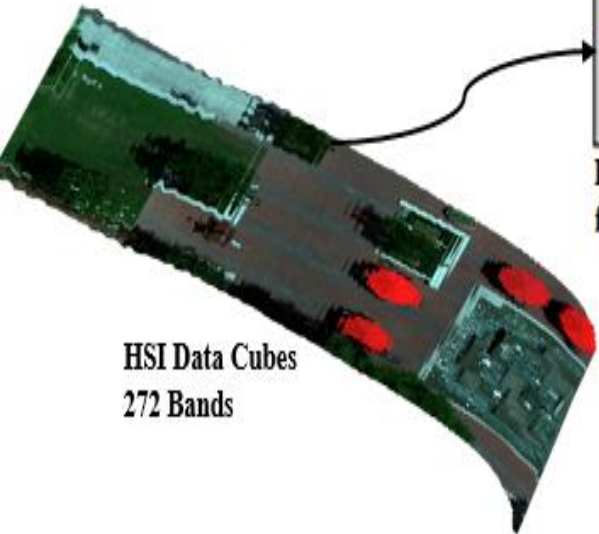


U.S. ARMY
RDECOM

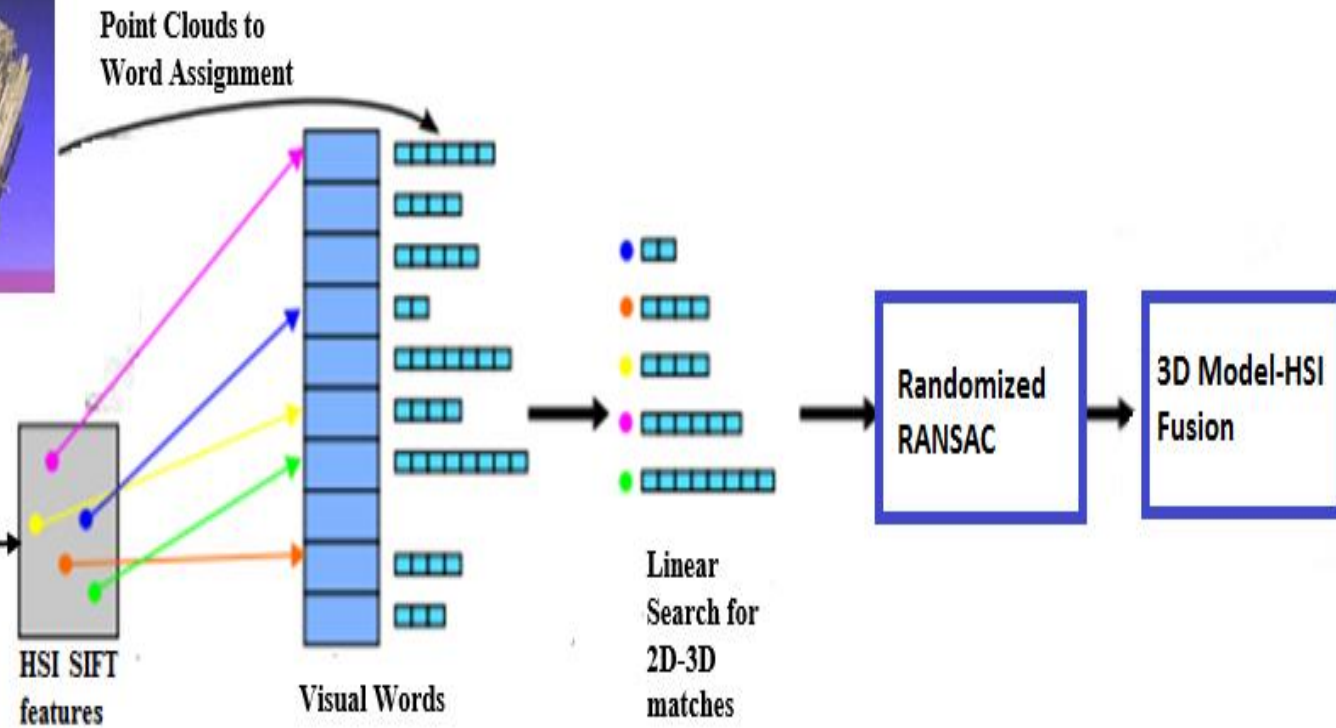
Fusion Approach



3D Model Reconstruction using Bundler & PMVS2



HSI Data Cubes
272 Bands





U.S. ARMY
RDECOM

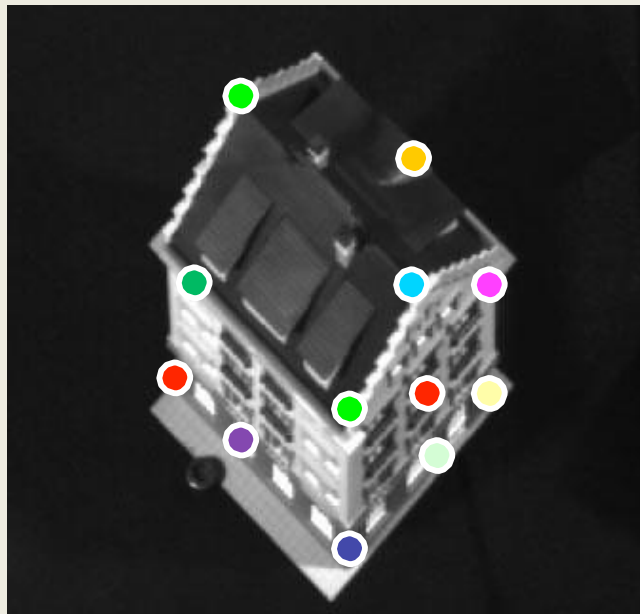
Model Fitting Approach



Goal: Given a query image I , find object model that matches with I

Model: Collection of points on planar surface

Query

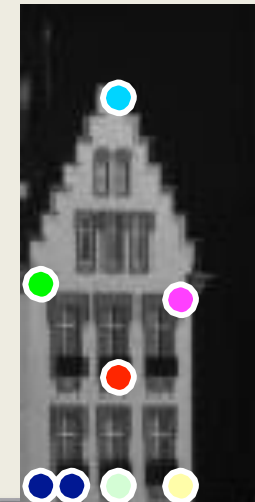


Invariant Spatial Features from
Phantom/GoPro Image

Invariant Spatial Features
from drone Aibotix/HS Imagery



Model 1



Model 2

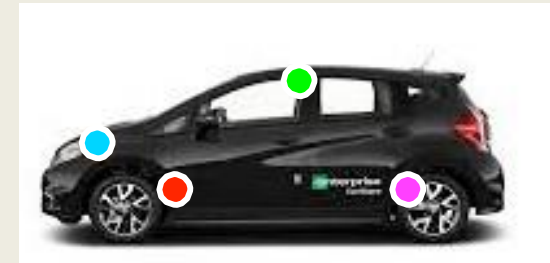
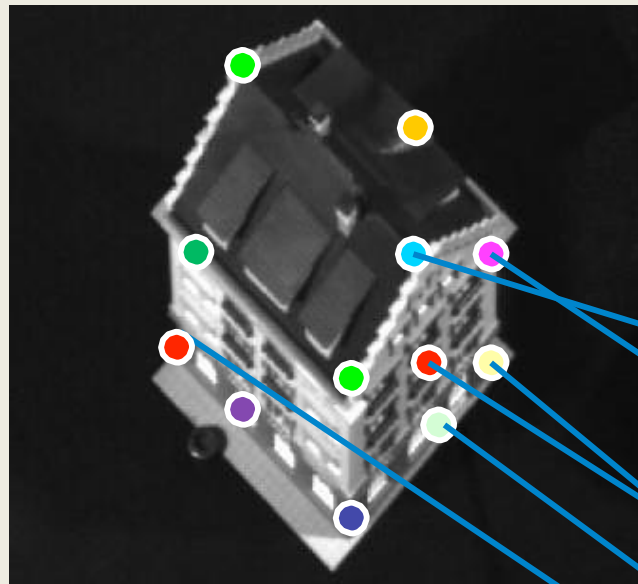
U.S. ARMY
RDECOM

Model Fitting Approach

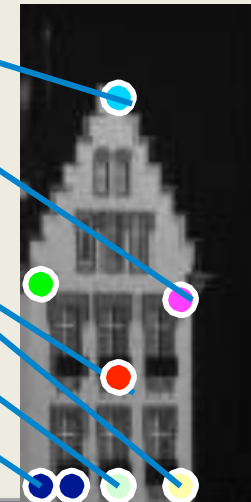
ARL

- Find matches between “model” points and “query” points
- Using N matches to fit homographic transformation
- If matches and selected model are correct, the fitting error is small

Query



Model 1

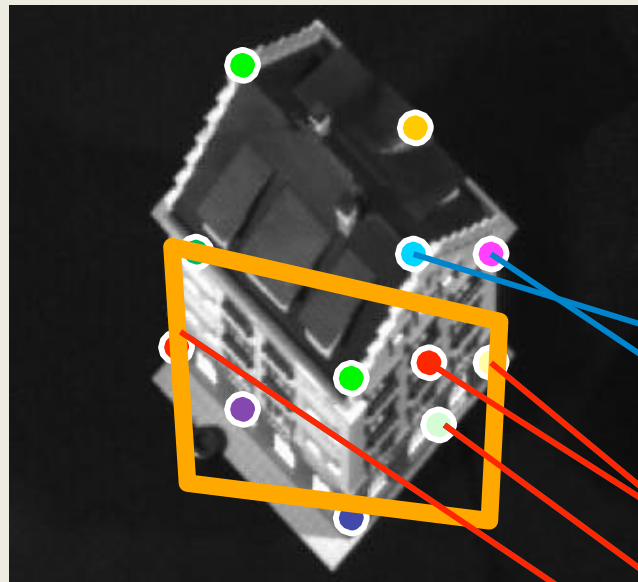


Model 2

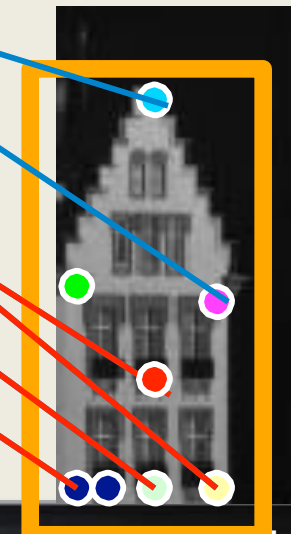


- Find matches between “model” points and “query” points
- Using N matches to fit homographic transformation
- If matches and selected model are correct, the fitting error is small

Query



- Generate hypothesis
- Verify hypothesis
- Select hypothesis with lowest fitting error
- Generate recognition results



Model 2

Verification: The hypothesis generates *high* fitting error



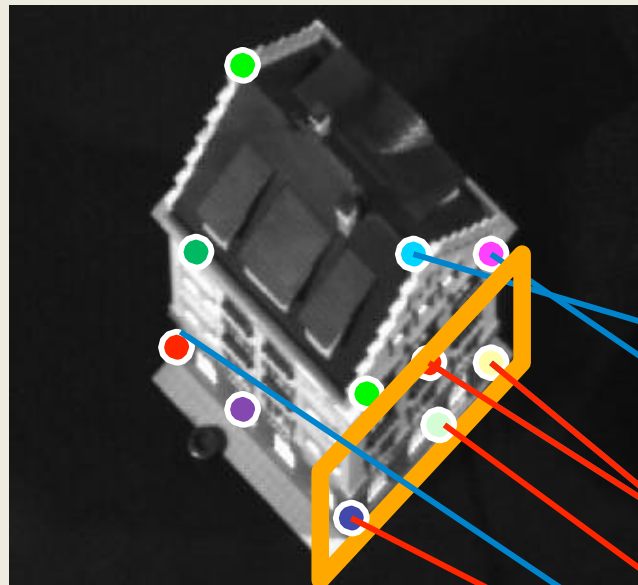
U.S. ARMY
RDECOM

Model Fitting Approach

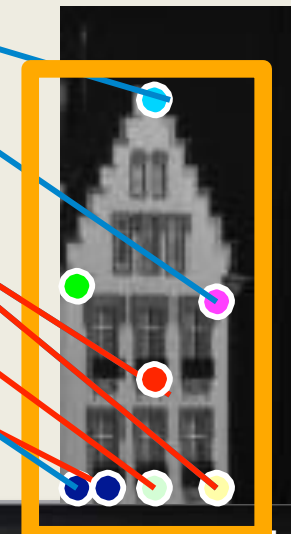
ARL

- Find matches between “model” points and “query” points
- Using N matches to fit homographic transformation
- If matches and selected model are correct, the fitting error is small

Query



- Generate hypothesis
- Verify hypothesis
- Select hypothesis with lowest fitting error
- Generate recognition results

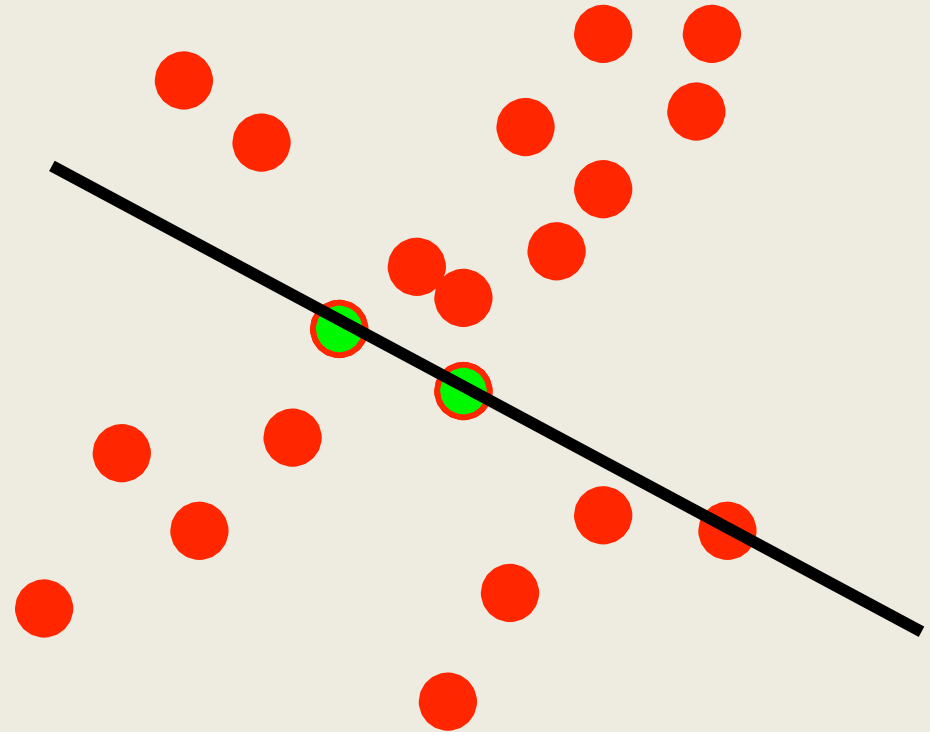


Model 2

Verification: The hypothesis generates *low* fitting error



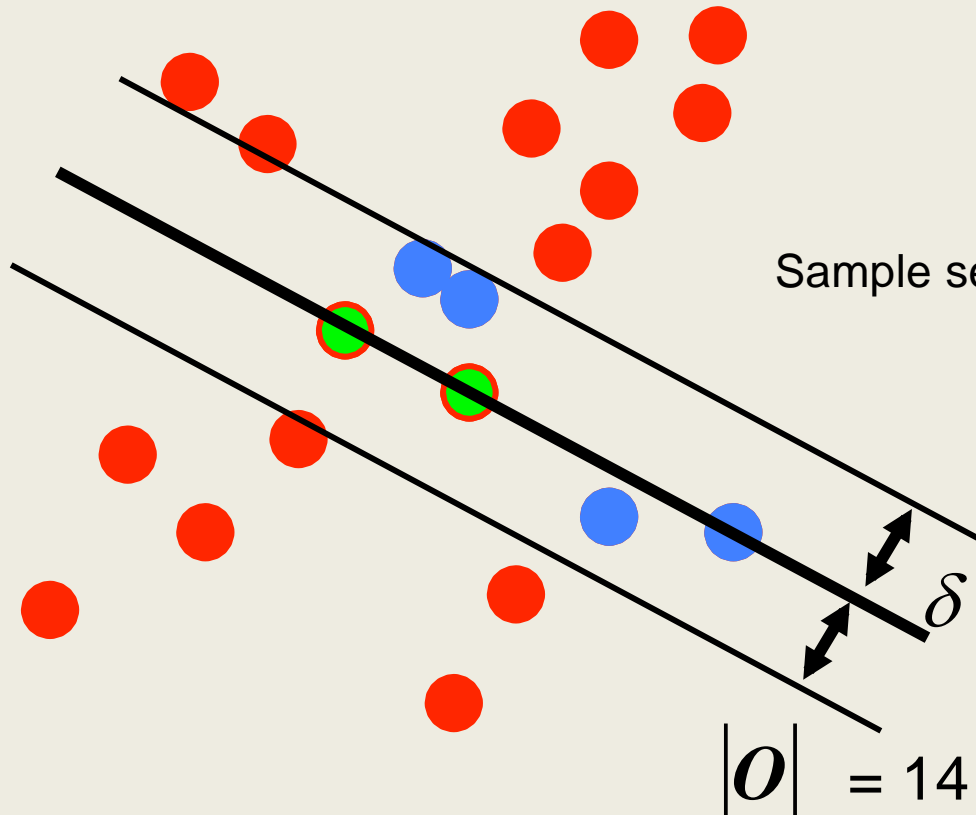
Random Sample Consensus (RANSAC)



Sample set = Set of points in 2D

Algorithm:

1. Select random sample of minimum required size to fit model
 2. Compute a putative model from sample set
 3. Compute the set of inliers to this model from whole data set
- Repeat 1-3 until model with the most inliers over all samples is found



Algorithm:

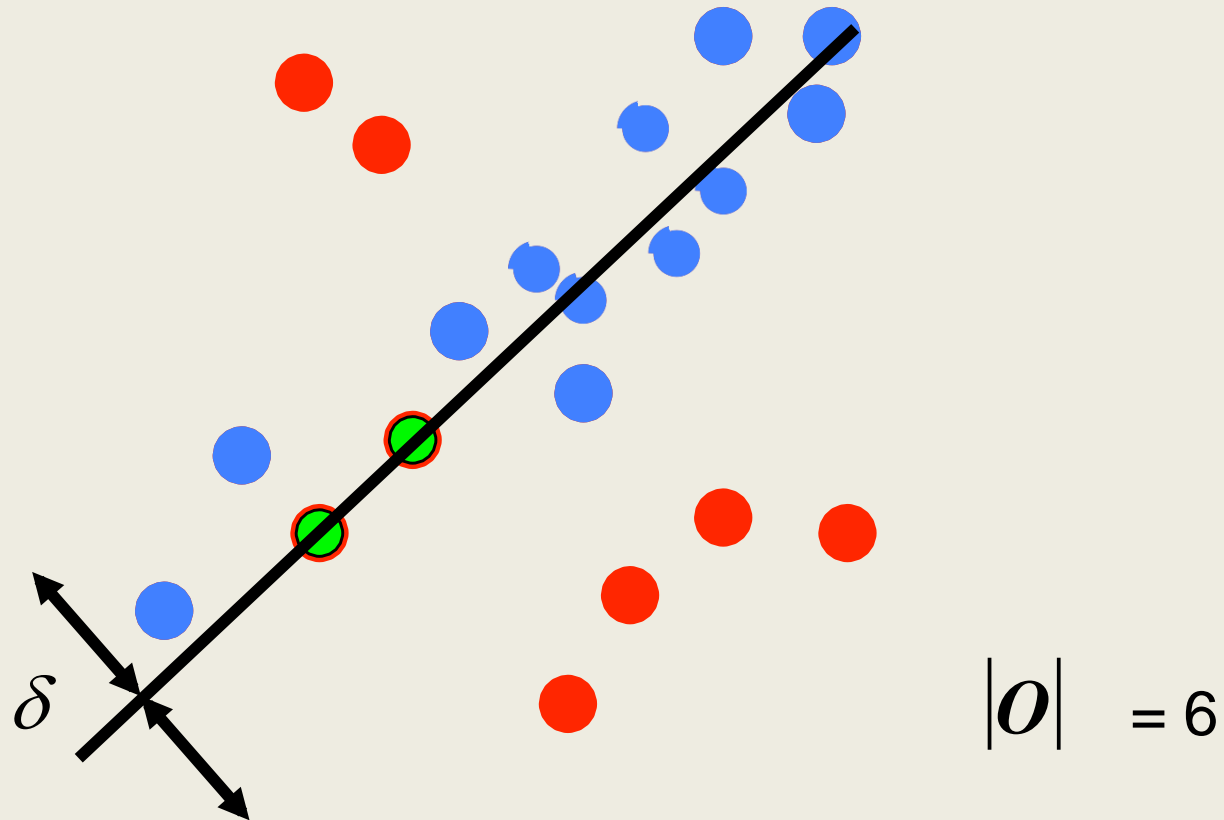
1. Select random sample of minimum required size to fit model
 2. Compute a putative model from sample set
 3. Compute the set of inliers to this model from whole data set
- Repeat 1-3 until model with the most inliers over all samples is found



U.S. ARMY
RDECOM

RANSAC

ARL



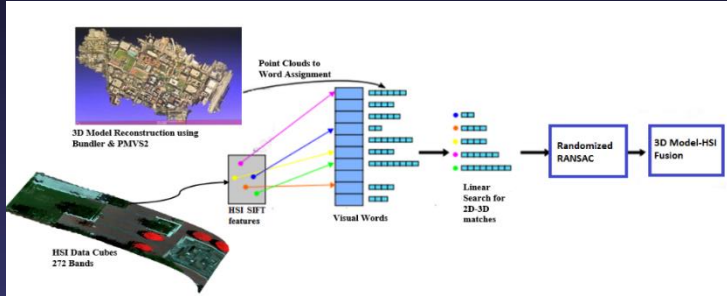
Algorithm:

1. Select random sample of minimum required size to fit model
 2. Compute a putative model from sample set
 3. Compute the set of inliers to this model from whole data set
- Repeat 1-3 until model with the most inliers over all samples is found



U.S. ARMY
RDECOM

Fusion of 3D Structure & Spectra



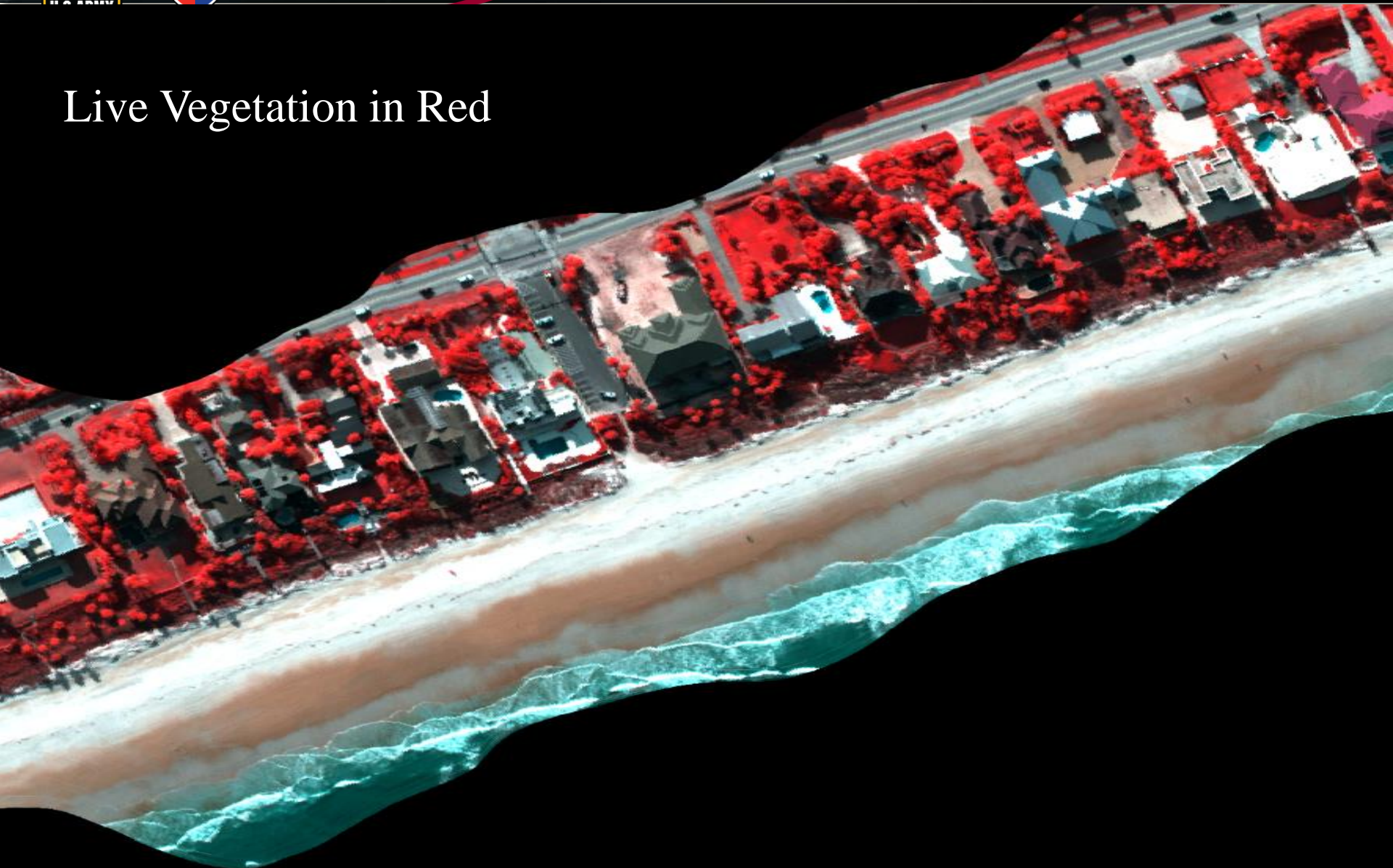
Geo-registration *not* required



U.S. ARMY
RDECOM

Geo-Based Fusion of 3D DEM & Spectra **ARL**

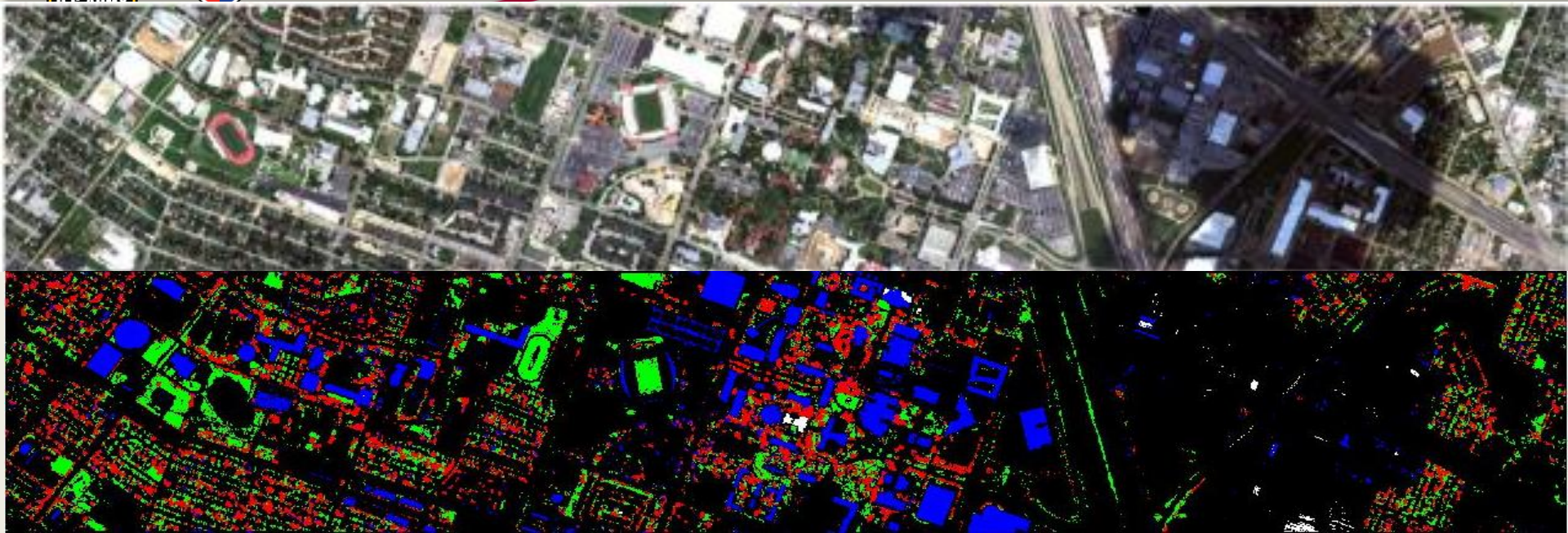
Live Vegetation in Red





U.S. ARMY
RDECOM

Rule-Based Image Segmentation **ARL**



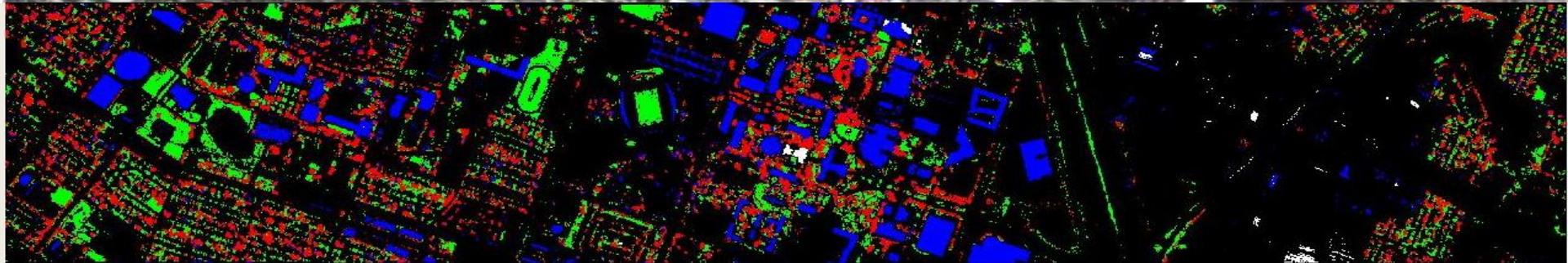
Predefined Classes

Class	Spectral Property	Height Property
Trees	High Vegetation Index	High
Grass	High Vegetation Index	Low
Water	High Water Index	Low
Buildings	Low Vegetation Index	High
Unknown	Low Vegetation Index	Low



U.S. ARMY
RDECOM

Adaptive Machine Learning & Target Localization



Autonomous Background Sampling





Dataset

Collected drone based USC hyperspectral dataset & USC-ICT 3D DEM for research and algorithm development

Algorithmic Approach

- Fusion of 3D structure & hyperspectral data
- Spectral & height rule based image segmentation
- Unsupervised selection of background material spectra using segmented map
- [Adaptive machine learning](#)

Impact

Adaptive, Aerial Image Understanding

- Material classification maps for Common Operating Picture (COP)
- Target material localization

Follow Up

- Adapt approach to [SWIR Hyperspectral data](#) and 3D Point Clouds (e.g., LiDAR, Photogrammetry)
- Enhance situational awareness via 3D augmented reality visualization (e.g., Microsoft HoloLens)