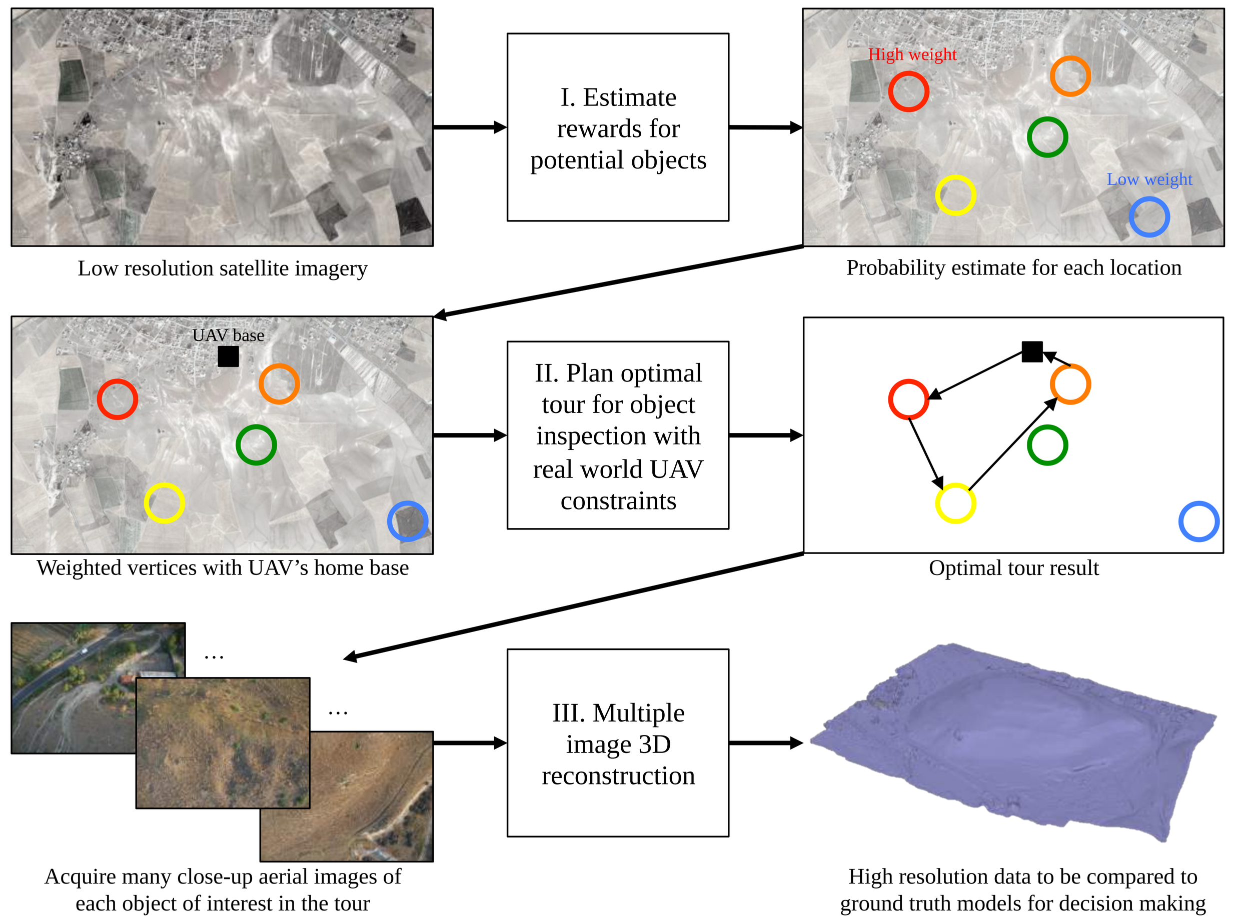
A Multi-Resolution Approach for Discovery and 3D Modeling of Archaeological Sites Using Satellite Imagery and a UAV-borne Camera

NSF 1330008 CPS, PI: Venkatesh Saligrama (srv@bu.edu), Co-PI David Castanon, Co-PI Mac Schwager
College of Engineering, Boston University

Boston University

Introduction

- **Motivation**: Team of archaeologists at BU who are interested in studying burial mound structures from the ancient Lydian civilizations currently located in Turkish countryside
- **Problem**: Some burial mound locations ar known, but the country side is too vast to sen specialized teams of workers to inspect eac potential future dig site
- **Current Technology**: Coarse satellite imagery
- **Proposed Solution**: Three stage method fc discovering new sites using autonomous aeria vehicle submitted to ACC 2016 [1]:
  - **I**: Utilize low resolution satellite im agery coupled with machine learning a gorithms to perform a coarse search an identify tentative locations of interest
  - **II**: Plan an optimal trajectory using prev ous weights to inspect closely promisin objects subject to fuel constraints
  - **III**: Generate 3-D reconstructions of the area of interest in order to finally classifi-



I – Learning

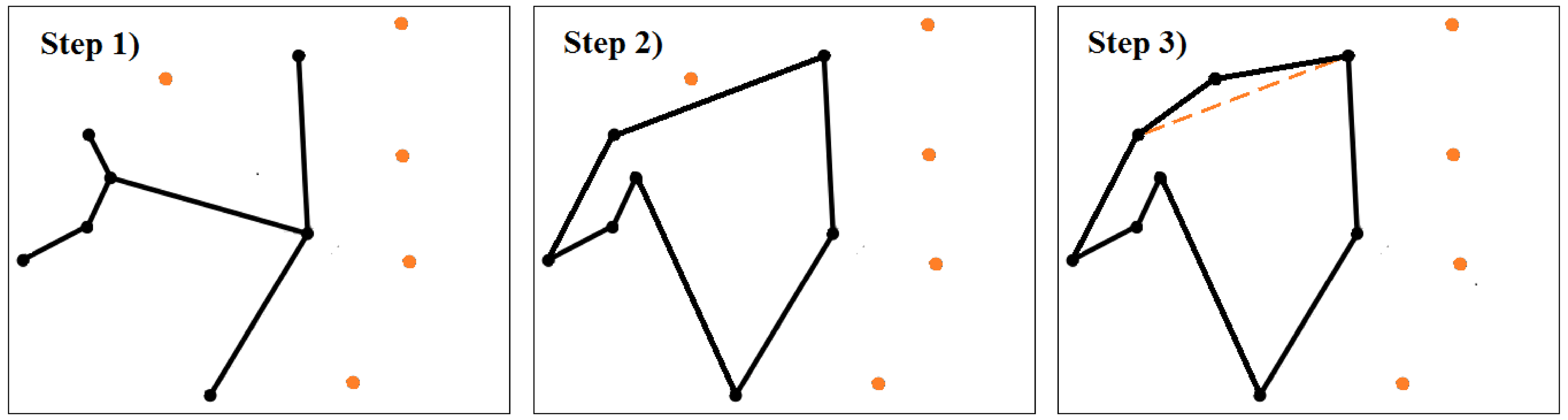
- Standard binary learning problem
- Training examples: $(x_1, y_1), \ldots, (x_n, y_n)$ where $x_i \in \mathcal{R}^d$ and $y_i \in \{0, 1\}$
- Learn a classifer: $f = sign(w^T x)$
- $\hat{w} = \arg\max_w \frac{1}{n} \sum_{i=1}^{n} \log(1 + \exp(-y_i w^T x_i))$
- Probability estimate for location i: $\hat{p}(x_i) = \frac{1}{1+\exp(-\hat{w}^T x_i)}$
- Entropy as reward for location i: $H(\hat{p}(x_i)) = -\hat{p}(x_i)\log(\hat{p}(x_i)) - (1 - \hat{p}(x_i))\log(1 - \hat{p}(x_i))$

II – Path Planning

- Orienteering problem:
  - $G = (V, E)$ where $V = \{v_1, \ldots, v_n\}$ and $E = \{(v_i, v_j), i < j\}$; Start and end node: v_1
  - Node reward: $r_i \equiv H(\hat{p}(x_i))$; Expanded edge cost: c_{ij}; Budget on cost: B
  - **Objective**: Maximize the total rewards of the nodes being visited without exceeding the cost budget

II – Path Planning (Cont)

- New algorithm:
  - Step 1): Grow a tree to visit nodes of high marginal reward within the budget
  - Step 2): Run Lin-Kernighan-Helsgaun algorithm to find a tour on the nodes of the tree
  - Step 3): Exploit leftover budget and insert more nodes into the tour

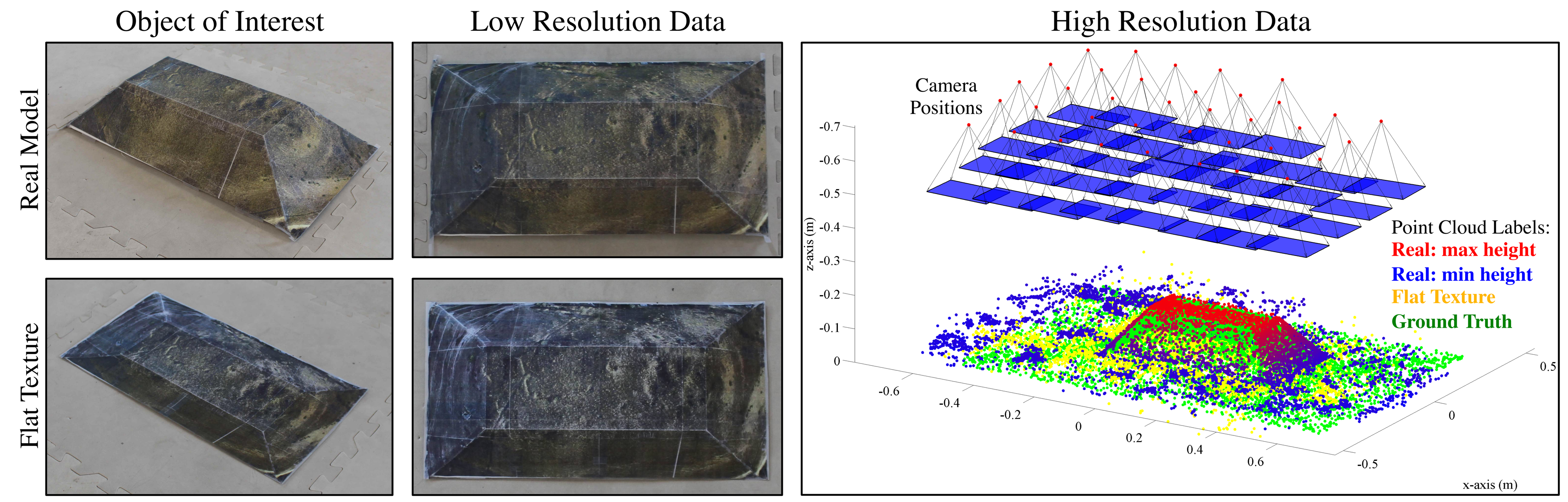


III – Multiple View 3-D Reconstruction

- **Input**: Images I_k, $k = 1, \ldots, m$ taken of the same $\mathbf{P}^i \in \mathbb{R}^3$, $i = 1, \ldots, n$ world features.
  - Pixel position of i^{th} world feature in camera k ($\mathbf{p}_k^i$) are given by the pinhole camera model: $\lambda_k^i \begin{bmatrix} \mathbf{p}_k^i \\ 1 \end{bmatrix} = \mathbf{K}\mathbf{P}_k^i$
- **Objective**: Estimate the relative transformations $(\mathbf{R}_{k1}, \mathbf{t}_k)$ between the k^{th} camera frame and the reference frame (camera 1) as well as the unknown feature depths (λ_1^i) such that the following reprojection error from the estimated 3D points is minimized,

$$\sum_{k=1}^{m} \sum_{i=1}^{n} \alpha_{ik} \left\| \lambda_k^i \mathbf{p}_k^i - \mathbf{K}\left(\mathbf{R}_{k1}(\lambda_1^i \mathbf{K}^{-1} \mathbf{p}_i^k) + \mathbf{t}_k\right) \right\|^2$$

- **Solution**: Utilize Levenberg−Marquardt algorithm with accurate initialization from two-view epipolar geometry and least squares estimation given the image features that were extracted and matched among the images.
- **Results**: Comparison of 3D reconstruction of two different objects with similar low-resolution data
  - Iterative Closest Point algorithm computed mean distances from the ground truth data to the real model ($\sim 0.08m$) and the flat texture ($\sim 0.18m$)



References

[1] H. Ding, E. Cristofalo, J. Wang, D. Castañon, E. Montijano, V. Saligrama, and M. Schwager, "A multi-resolution approach for discovery and 3d modeling of archaeological sites using satellite imagery and a uav-borne camera," in *2016 American Control Conference (ACC)*, Submitted Sept. 2015.