3D DENSE MAPPING AND LOCALIZATION WITH ICP

Max Lu

April 26 2016

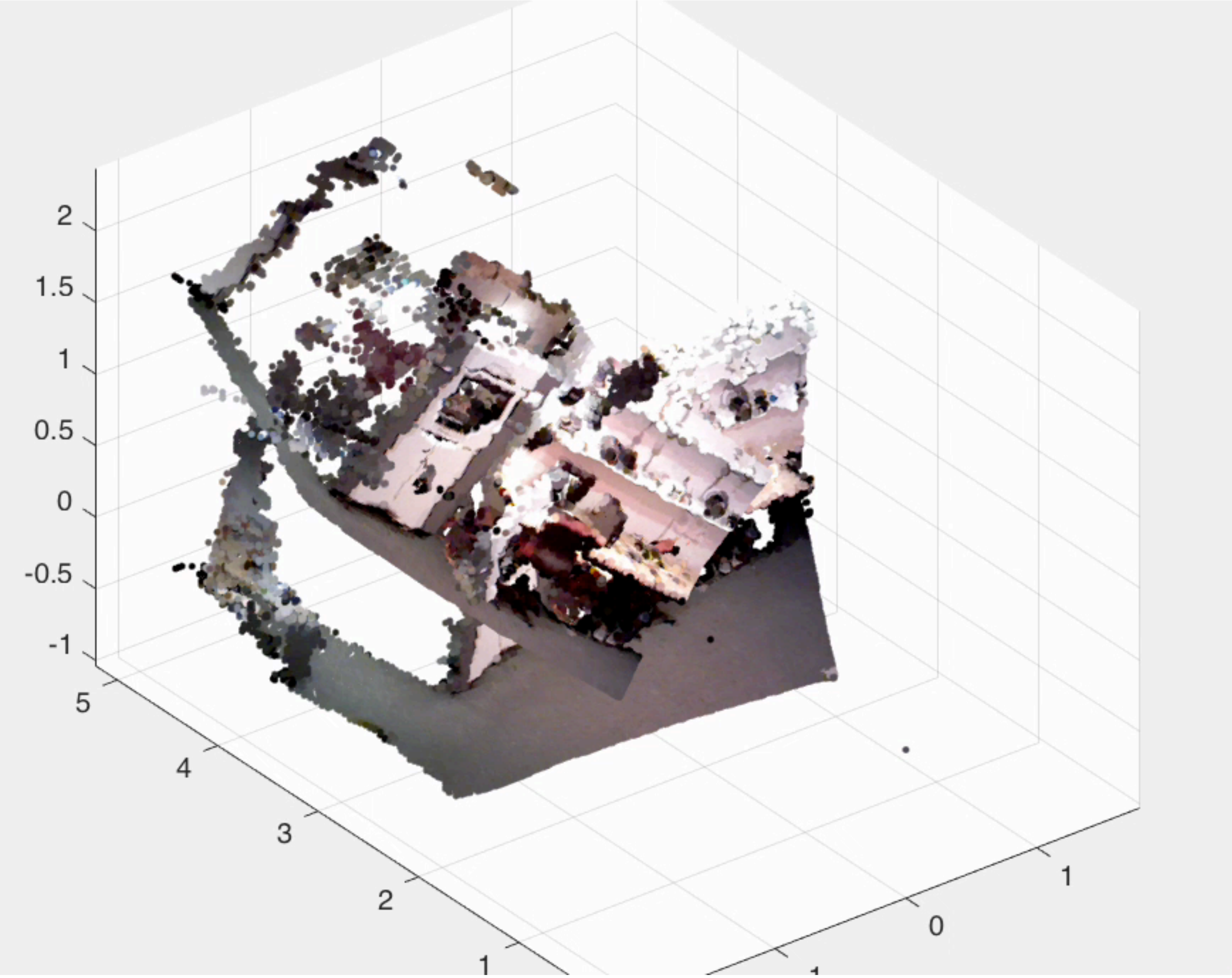
PROJECT OVERVIEW

- RGB-D Dataset
- Iterative Closest (Corresponding) Points
- Mapping and Localization

ICP

- Sampling
- Matching
- Weighting
- Rejection
- Optimization

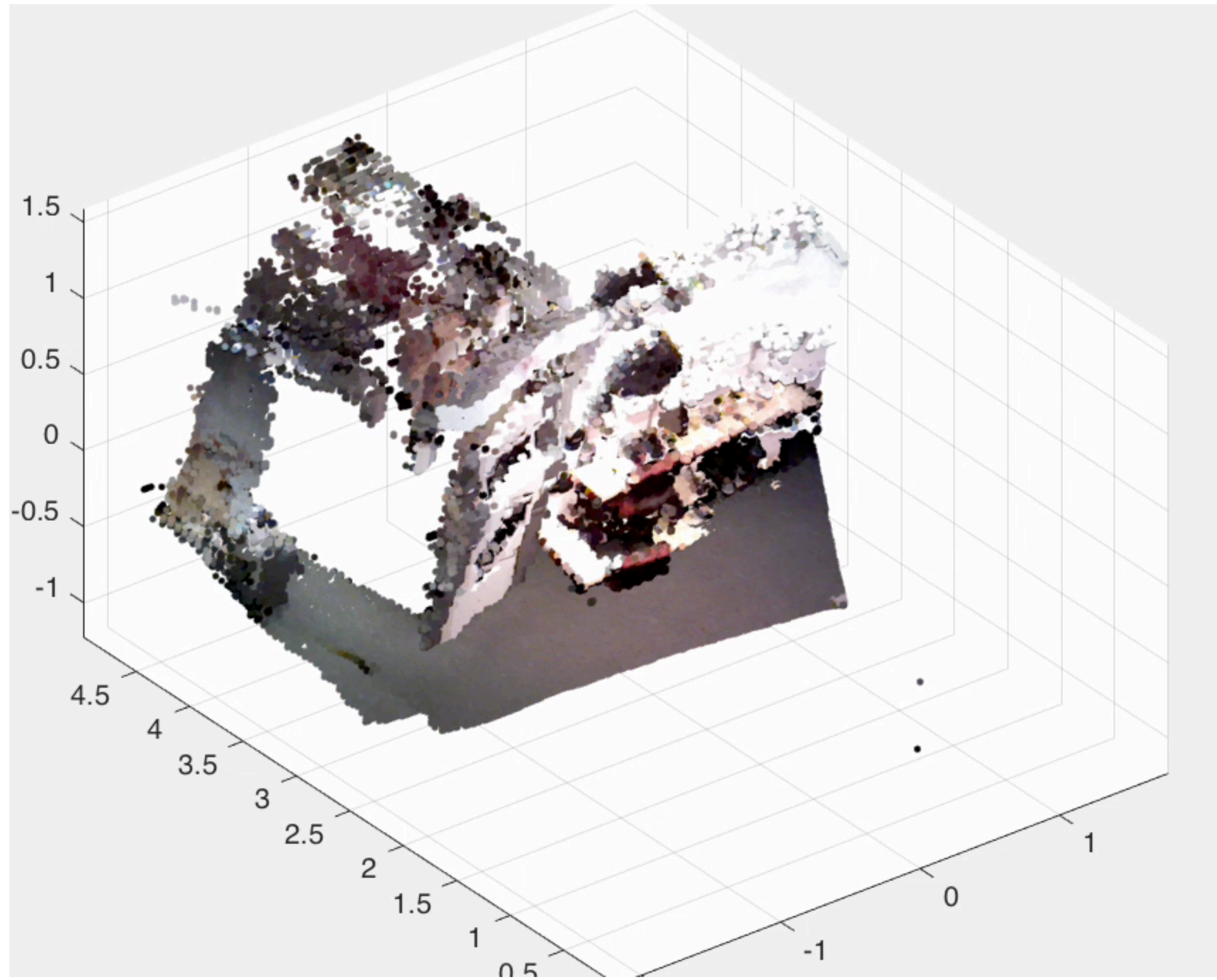
Frame 1 vs Frame 1



ICP

- *Sampling*
- *Matching*
- *Weighting*
- *Rejection*
- *Optimization*

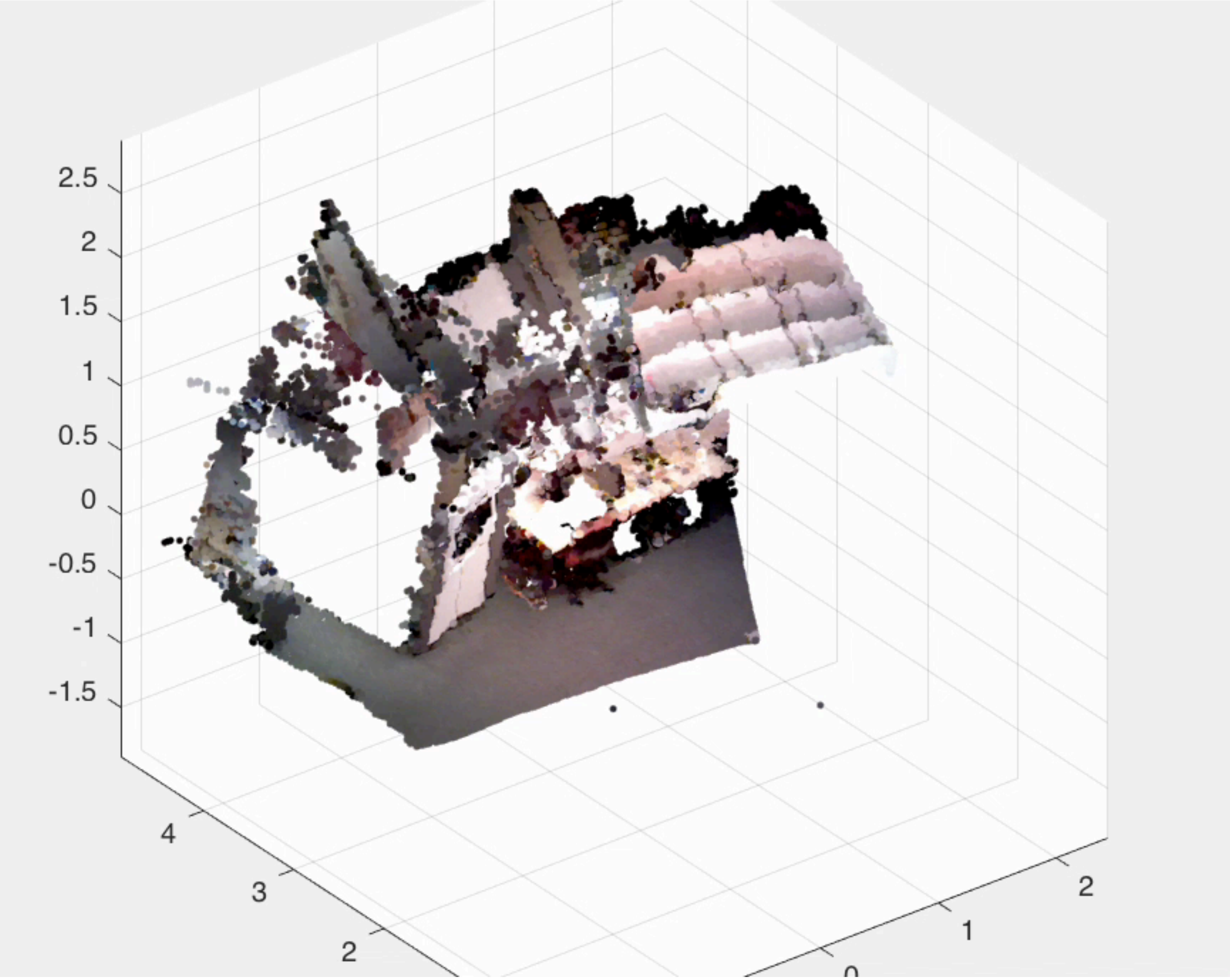
Frame 1 vs Frame 50



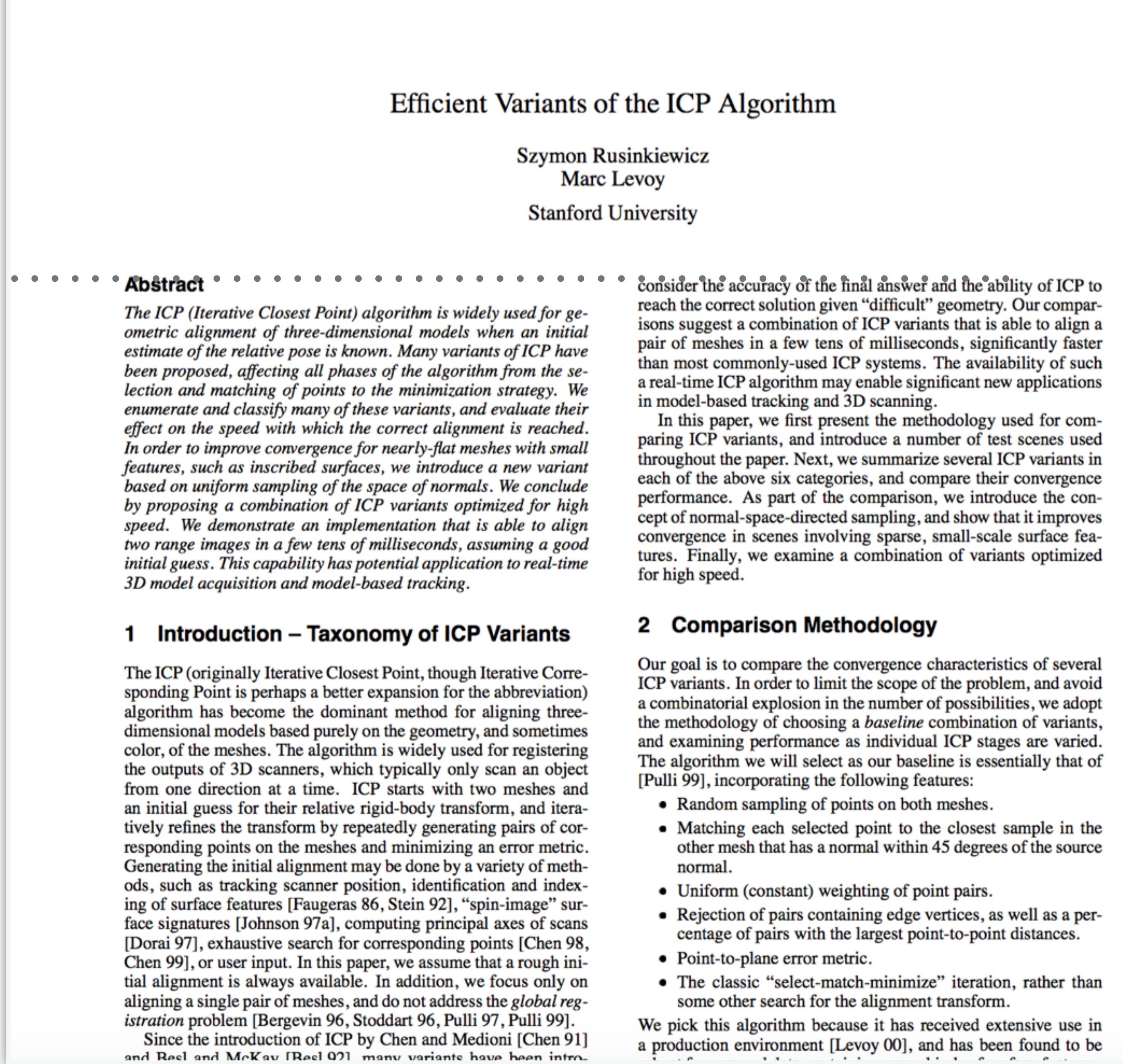
ICP

Frame 1 vs Frame 50

- Sampling
- Matching
- Weighting
- Rejection
- Optimization



ICP – SAMPLING



Efficient Variants of the ICP Algorithm

Szymon Rusinkiewicz
Marc Levoy

Stanford University

Abstract

The ICP (Iterative Closest Point) algorithm is widely used for geometric alignment of three-dimensional models when an initial estimate of the relative pose is known. Many variants of ICP have been proposed, affecting all phases of the algorithm from the selection and matching of points to the minimization strategy. We enumerate and classify many of these variants, and evaluate their effect on the speed with which the correct alignment is reached. In order to improve convergence for nearly-flat meshes with small features, such as inscribed surfaces, we introduce a new variant based on uniform sampling of the space of normals. We conclude by proposing a combination of ICP variants optimized for high speed. We demonstrate an implementation that is able to align two range images in a few tens of milliseconds, assuming a good initial guess. This capability has potential application to real-time 3D model acquisition and model-based tracking.

1 Introduction – Taxonomy of ICP Variants

The ICP (originally Iterative Closest Point, though Iterative Corresponding Point is perhaps a better expansion for the abbreviation) algorithm has become the dominant method for aligning three-dimensional models based purely on the geometry, and sometimes color, of the meshes. The algorithm is widely used for registering the outputs of 3D scanners, which typically only scan an object from one direction at a time. ICP starts with two meshes and an initial guess for their relative rigid-body transform, and iteratively refines the transform by repeatedly generating pairs of corresponding points on the meshes and minimizing an error metric. Generating the initial alignment may be done by a variety of methods, such as tracking scanner position, identification and indexing of surface features [Faugeras 86, Stein 92], "spin-image" surface signatures [Johnson 97a], computing principal axes of scans [Dorai 97], exhaustive search for corresponding points [Chen 98, Chen 99], or user input. In this paper, we assume that a rough initial alignment is always available. In addition, we focus only on aligning a single pair of meshes, and do not address the *global registration* problem [Bergevin 96, Stoddart 96, Pulli 97, Pulli 99].

Since the introduction of ICP by Chen and Medioni [Chen 91] and Besl and McKay [Besl 92], many variants have been intro-

consider the accuracy of the final answer and the ability of ICP to reach the correct solution given "difficult" geometry. Our comparisons suggest a combination of ICP variants that is able to align a pair of meshes in a few tens of milliseconds, significantly faster than most commonly-used ICP systems. The availability of such a real-time ICP algorithm may enable significant new applications in model-based tracking and 3D scanning.

In this paper, we first present the methodology used for comparing ICP variants, and introduce a number of test scenes used throughout the paper. Next, we summarize several ICP variants in each of the above six categories, and compare their convergence performance. As part of the comparison, we introduce the concept of normal-space-directed sampling, and show that it improves convergence in scenes involving sparse, small-scale surface features. Finally, we examine a combination of variants optimized for high speed.

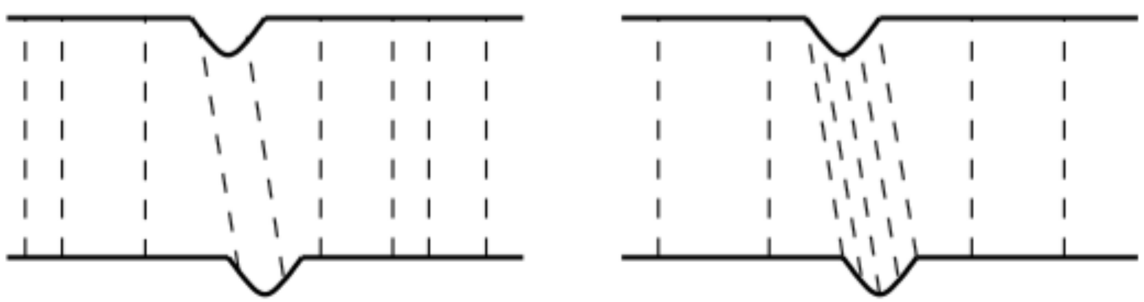
2 Comparison Methodology

Our goal is to compare the convergence characteristics of several ICP variants. In order to limit the scope of the problem, and avoid a combinatorial explosion in the number of possibilities, we adopt the methodology of choosing a *baseline* combination of variants, and examining performance as individual ICP stages are varied. The algorithm we will select as our baseline is essentially that of [Pulli 99], incorporating the following features:

- Random sampling of points on both meshes.
- Matching each selected point to the closest sample in the other mesh that has a normal within 45 degrees of the source normal.
- Uniform (constant) weighting of point pairs.
- Rejection of pairs containing edge vertices, as well as a percentage of pairs with the largest point-to-point distances.
- Point-to-plane error metric.
- The classic "select-match-minimize" iteration, rather than some other search for the alignment transform.

We pick this algorithm because it has received extensive use in a production environment [Levoy 00], and has been found to be

- Random Sampling (a)
- Normal-space Sampling (b)



(a) (b)

Compute Normals

4-NN 3d points

PCA

Sampling

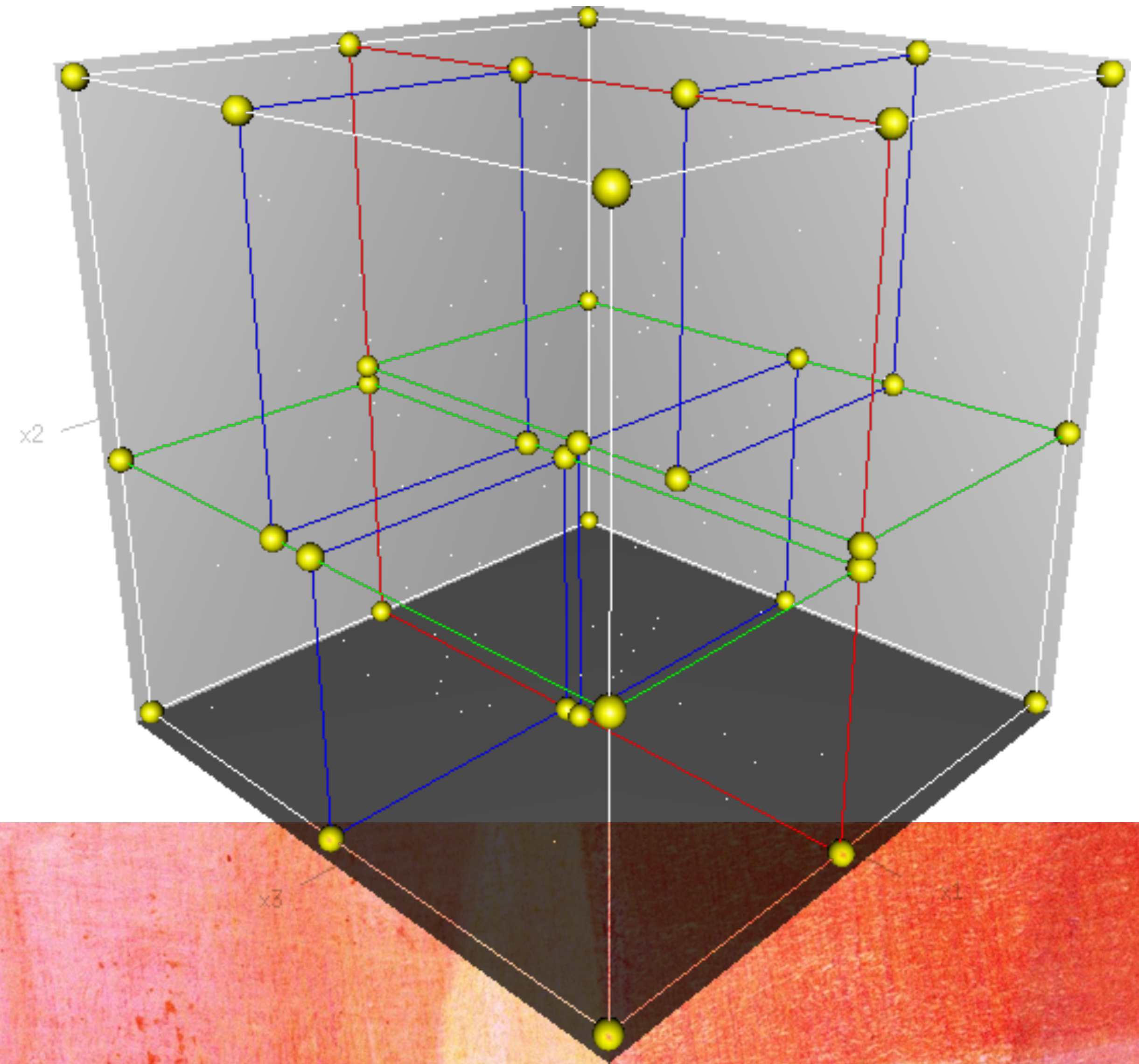
Convert 3d normals into 2d spherical coordinates

Binning all the normals

Uniform Sampling from bins

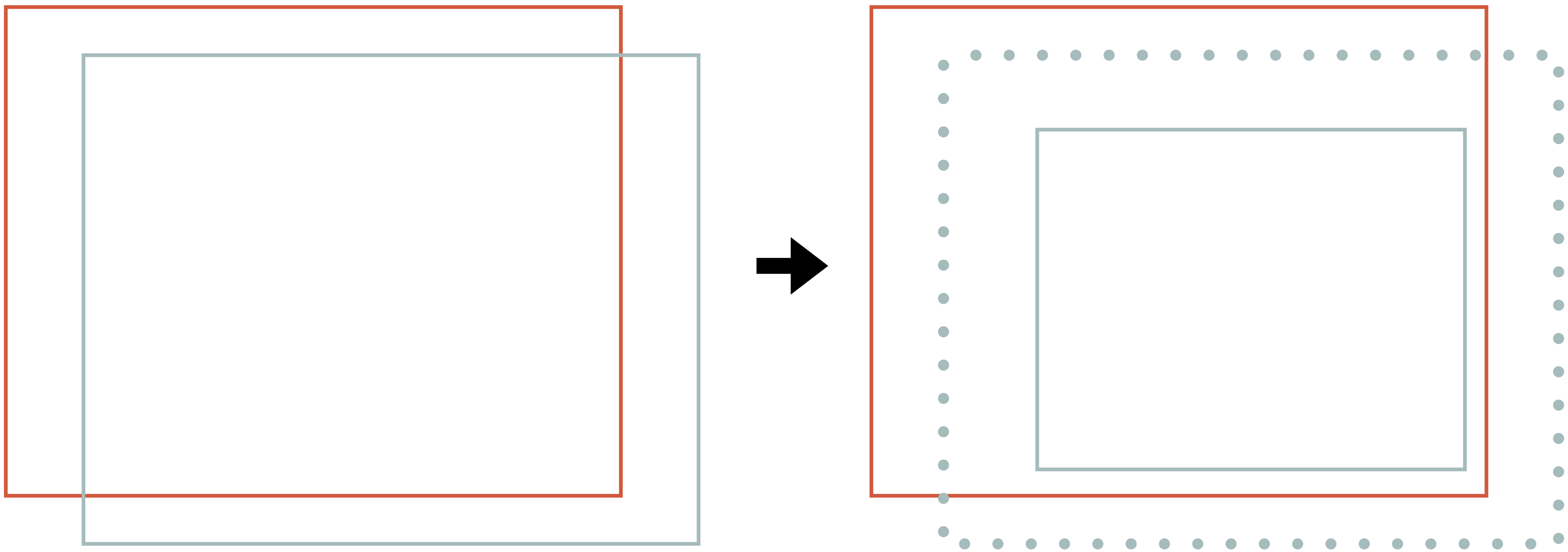
ICP – MATCHING

- Nearest Neighbor
- XYZ-RGB space
- K-d tree to accelerate the computation (Faster than KNN!)



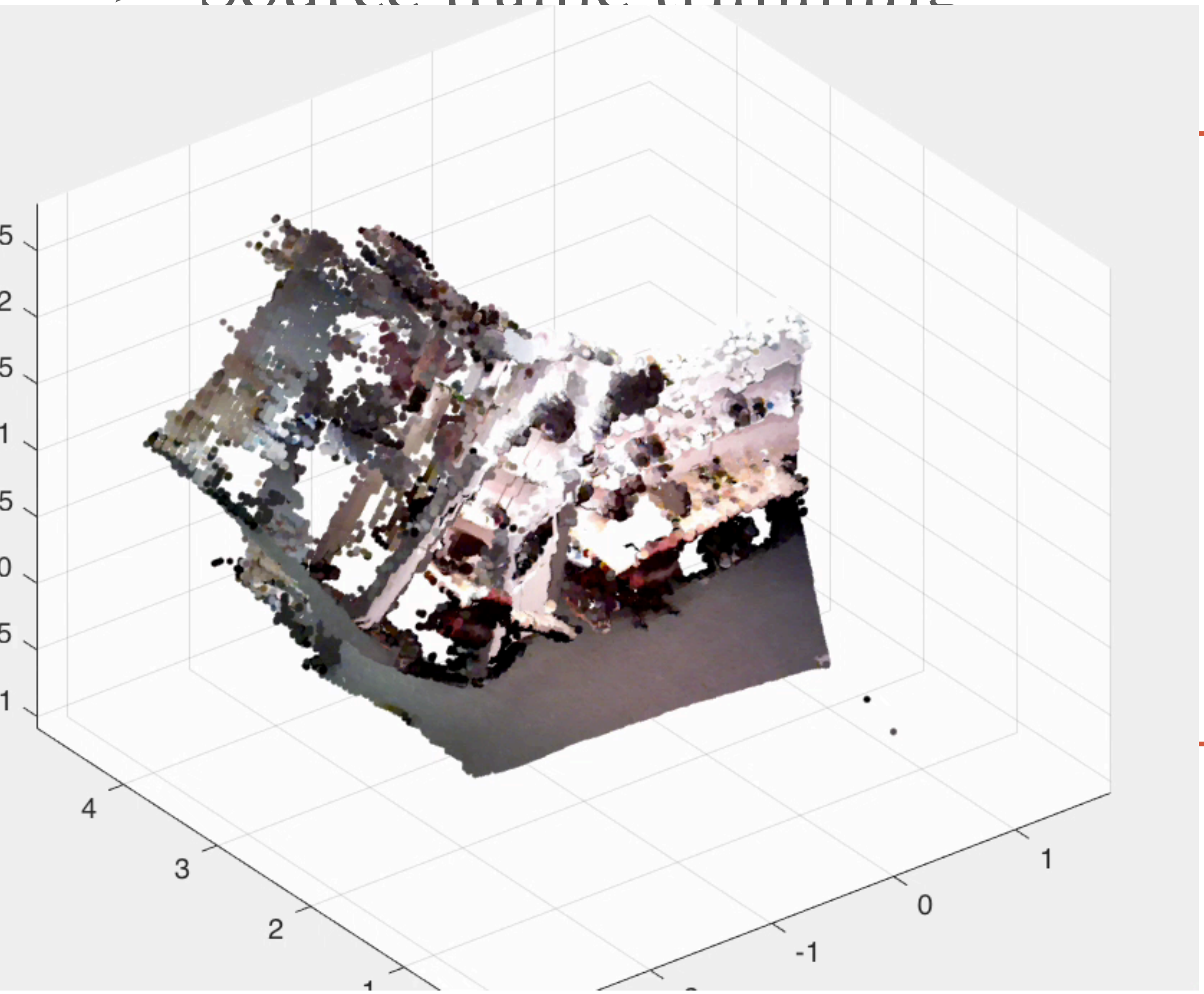
ICP - REJECTION

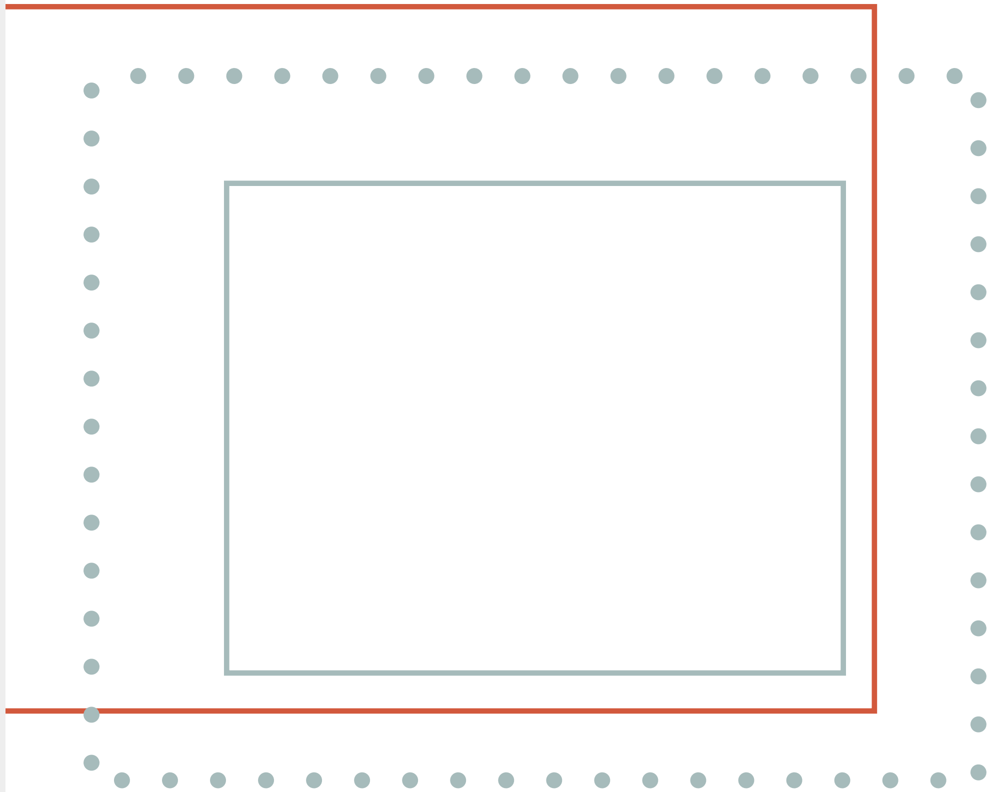
- Normal incompatibility (angle between normals > 45 degree)
- Source frame trimming



ICP – REJECTION

- Normal incompatibility (angle between normals > 45 degree)
- Source frame trimming





ICP – OPTIMIZATION METRIC

- Least Squares
- Point 2 Plane

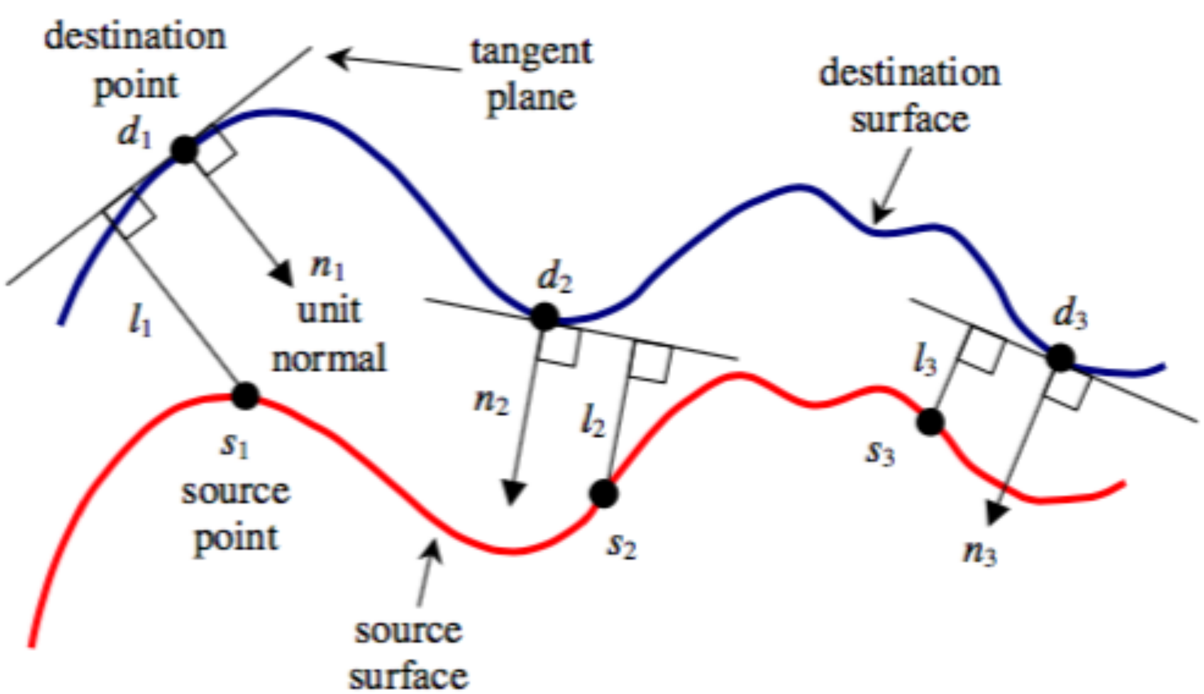


Figure 1: Point-to-plane error between two surfaces.

Technical Report TR04-004, Department of Computer Science, University of North Carolina at Cha

Linear Least-Squares Optimization for Point-to-Plane ICP Surface Registration

Kok-Lim Low

Department of Computer Science
University of North Carolina at Chapel Hill
Email: lowk@cs.unc.edu

ABSTRACT

The Iterative Closest Point (ICP) algorithm that uses the point-to-plane error metric has been shown to converge much faster than one that uses the point-to-point error metric. At each iteration of the ICP algorithm, the change of relative pose that gives the minimal point-to-plane error is usually solved using standard nonlinear least-squares methods, which are often very slow. Fortunately, when the relative orientation between the two input surfaces is small, we can approximate the nonlinear optimization problem with a linear least-squares one that can be solved more efficiently. We detail the derivation of a linear system whose least-squares solution is a good approximation to that obtained from a nonlinear optimization.

1 INTRODUCTION

3D shape alignment is an important part of many applications. It is used for object recognition in which newly acquired shapes in the environment are fitted to model shapes in the database. For reverse engineering and building real-world models for virtual reality, it is used to align multiple partial range scans to form models that are more complete. For autonomous range acquisition, 3D registration is used to accurately localize the range scanner, and to align data from multiple scans for view-planning

In [Rusinkiewicz01], it was sug
orientation (rotation) between the t
can approximate the nonlinear leas
with a linear one, so as to spe
approximation is simply done by re
1 in the rotation matrix.

In this technical report, we descri
system of linear equations to appr
system, and demonstrate how th
linear system can be obtained
decomposition). A 3D rigid-body
constructed from the linear least-sq

2 POINT-TO-PLANE IC

Given a source surface and a desti
the ICP algorithm first establishes
between points in the source surfa
surfaces. For example, for each p
nearest point on the destinatio
correspondence [Besl92] (see
approaches to find point correspon
iteration is a 3D rigid-body transfo
source points such that the total e

ICP – OPTIMIZATION

- Least Squares
- Point 2 Plane

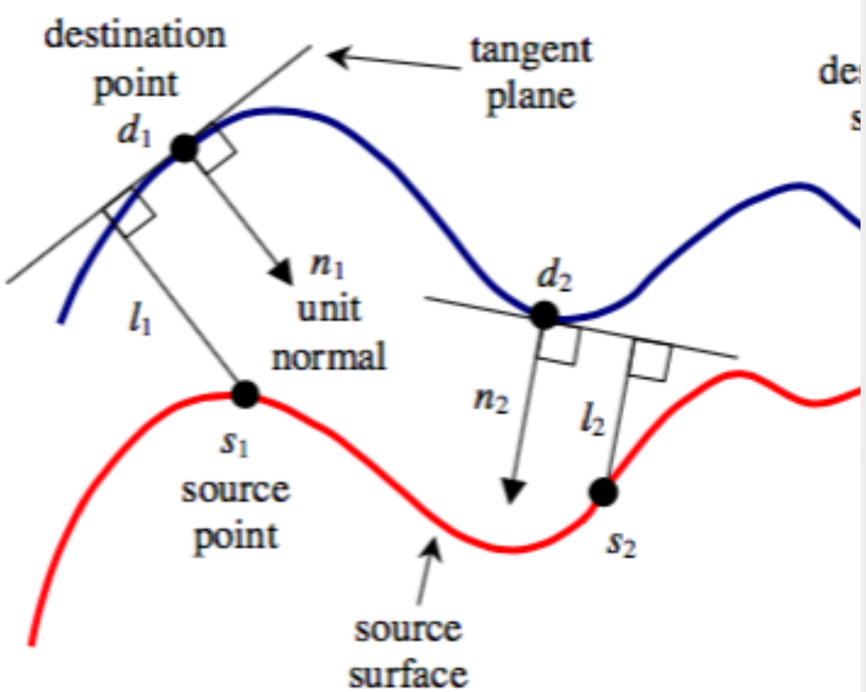
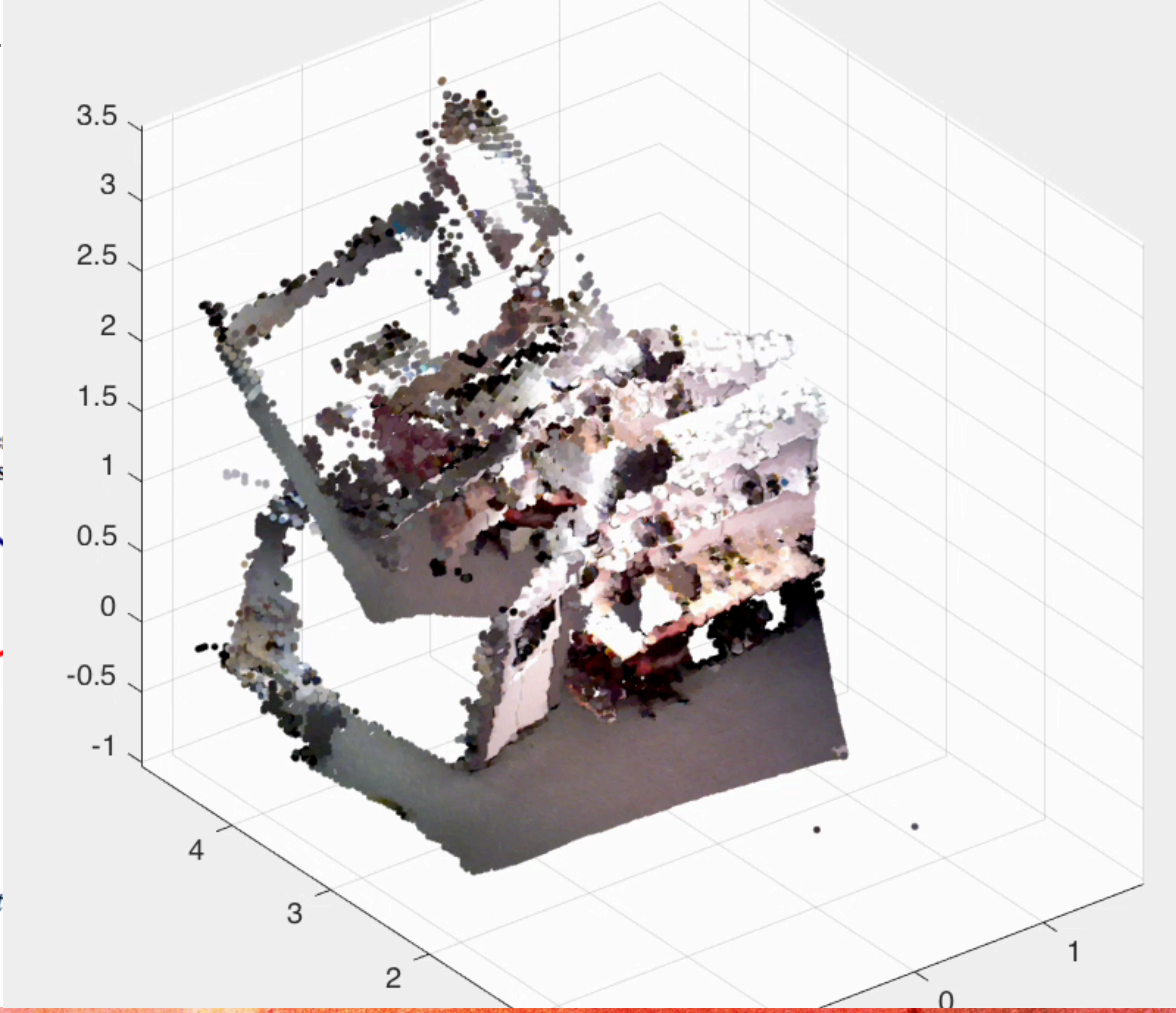


Figure 1: Point-to-plane error between t

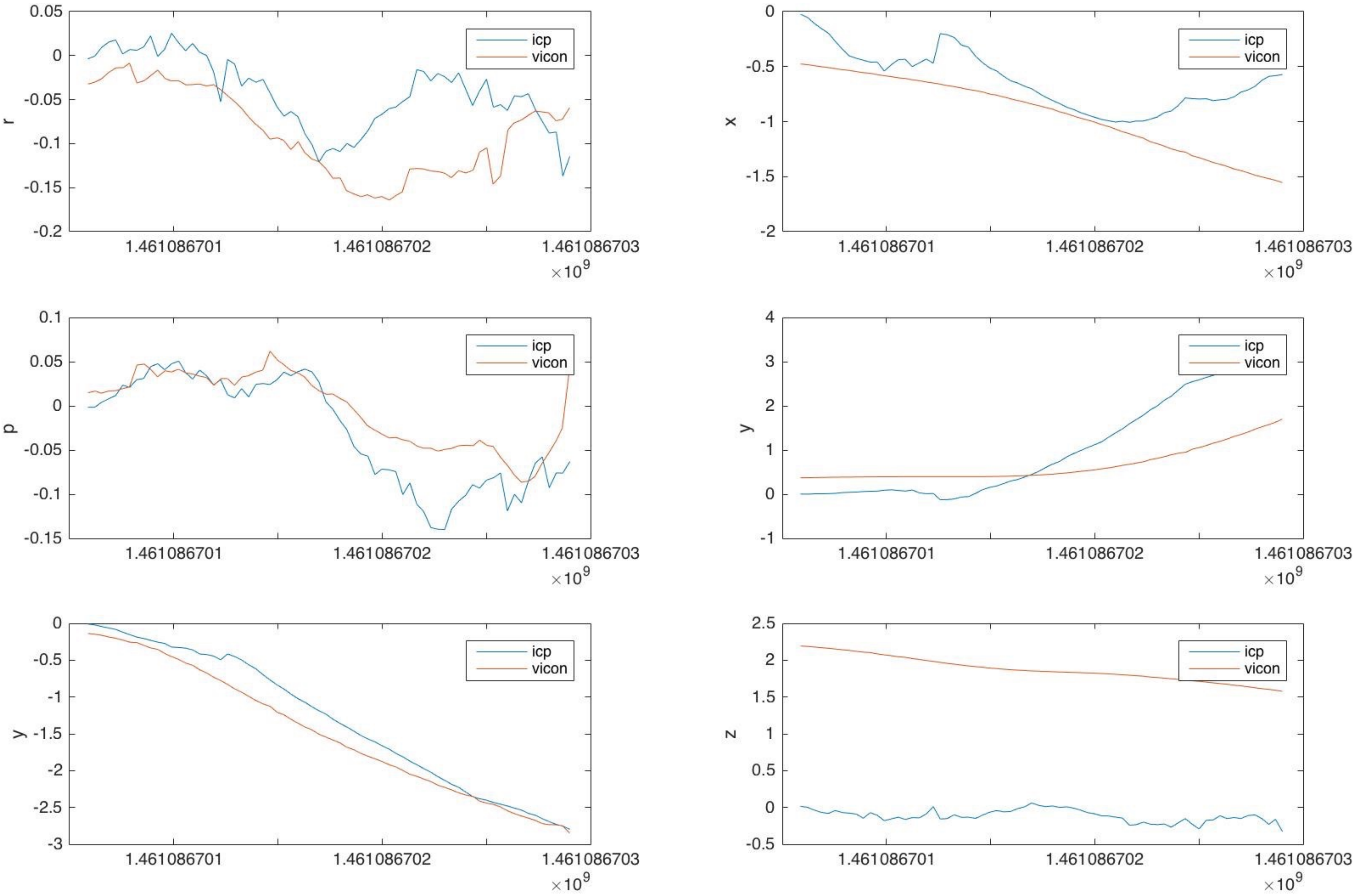


MAPPING & LOCALIZATION

- Vicon data
- Camera distortion & Noise
- Live Demo

MAPPING & LOCALIZATION

MAX LU 04/26/2016



NEXT STEP

- Global registration
- Feature-based sampling, matching, & Rejection (Plane estimation, etc)
- Model de-noising and smoothing
- Merge Vicon data (EKF etc. ?)

THANK YOU!

MAX LU 04/26/2016