# Coupled Joint Registration and Co-segmentation for Indoor Rigid Object Sets

Siyu Hu*

## Abstract

**Keywords:** Co-segmantion, Joint Registration

**Concepts:** •**Computing methodologies** → **Image manipulation;** *Computational photography;*

## 1 Introduction

## 2 Related Work

### 2.1 Functional Mapping

The Coupled Joint Registration and Co-segmentation problem addressed here is essentially a problem of point-to-point correspondence problem. A series of work based on the functional maps representation advocated in [Ovsjanikov et al. 2012] have be done. In one of the most recent work [], a convex relaxation technique was used to better approximate the global minimal for both rigid and non-rigid registration problem.

## 3 Method Overview

### 3.1 Problem Statement

Given a set of point clouds which record the same group of rigid indoor objects with different layout. We intend to samutaneously partition the point clouds into objects and align the points of same object to recover layouts for corresponding object. Figure 1 shows an example of input point clouds set.

### 3.2 Formulation

To formulate the relation between the unknown object set and the input point clouds. We come up with a generation model as follows:

$$P(v_{mi}) = \sum_{n=1}^{N} p_n \sum_{k=1}^{K_n} p_k N(\phi_{mn}(v_{mi})|x_k, \Sigma_k) \tag{1}$$

which means, The observed point clouds are generated by $N$ object model. Each object model is represented by a gaussian mixture model with $K_n$ centroids. Our goal is to maximize the probability of the expected compelete-data log-likelihood. The object function can be written as:

$$\Theta = \text{argmax} \sum_{Z} P(Z|V,\Theta) \ln P(V,Z;\Theta) \tag{2}$$

in which:

$$\Theta = \{\{p_n\}_{n=1}^{N}, \{p_k, x_k, \Sigma_k\}_{k=1}^{\sum K_n}, \{\phi_{mn}\}_{m=1,n=1}^{MN}\}$$

is the parameters of the generation model.
$p_n$ is the prior probability that the point is generated by the n-th object.
$p_k$ is the weight of the k-th Gaussian.
$x_k$ is the center of the k-th Gaussian.
$\Sigma_k$ is the standard deviation of the k-th Gaussian.
There are $\sum K_n$ Gaussian model in total and among them, $K_n$ Gaussian models belongs to object $n$.
$V$ is the M input point clouds.
$v_{mi}$ is the i-th point of the m-th point cloud.
$Z$ is a latent variable set defined as:

$$Z = \{z_{ij} | j = 1...M, i = 1...N_j\}$$

among which if $z_{ij} = k(k = 1...\sum K_n)$ assign the observation of $\phi_{mn}(v_{mi})$ to the k-th component of Gaussian mixture model.Such formulation can be seen as an extention of joint registration formulation in [**?**], upon which we add several gaussian mixture model together to express a group of objects. By solving this new problem we simutaneously solve the object co-segmentation of given observation.

## 4 Algorithms and Implementation

### 4.1 Expectation Conditional Maximization

Assuming the observed point clouds $\{V_m\}$ are independent and identically distributed, we can then write the (2) as:

$$\varepsilon(\Theta|V,Z) = \sum_{m,i,k} \alpha_{mik}(\log p_n + \log p_k + \log P(\phi_{nm}(v_{mi})|z_{ji} = k;\Theta)) \tag{3}$$

In which the $\alpha_{mik} = P(z_{mi} = k|v_{mi};\Theta)$,

**Algorithm 1** Joint Registration and Co-segmentation (JRCS)

**Input:**
$\{V_m\}$:Observed point clouds
$\{\alpha^0_{mik}\}$:Initial posterior probabilities
**Output:**
$\Theta^q$:Final parameter set

1. $q \leftarrow 0$
2. **repeat**
3. CM-step-a: Use $\alpha^q_{mik}$, $x^{q-1}_k$ to estimate $\{R^q_{mn}\}$ and $\{t^q_{mn}\}$
4. CM-step-b: Use $\alpha^q_{mik}$, $\{R^q_{mn}\}$ and $\{t^q_{mn}\}$ to estimate the Gaussian centers $x^q_k$
5. CM-step-c: Use $\alpha^q_{mik}$, $\{R^q_{mn}\}$ and $\{t^q_{mn}\}$ to estimate the covariances $\Sigma^q_k$
6. CM-step-d: Use $\alpha^q_{mik}$ to estimate the priors $p^q_k$,$p^q_n$
7. E-step: Use $\Theta^{q-1}$ to estimate posterior probabilities. $\alpha^q_{mik} = P(z_{mi}|v_{mi};\Theta^{q-1})$
8. $q \leftarrow q + 1$
9. **until** Convergence
10. **return** $\Theta^q$

### 4.2 Initialization Techniques

A key advantage motivates our formulation is that the soft correspondence can be initialized more flexiblely comparing to the typical initialization techniques such as landmark point pairs in regis-

*e-mail:sy891228@mail.ustc.edu.cn
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SIGGRAPH 2016 Posters, July 24-28, 2016, Anaheim, CA
ISBN: 978-1-4503-ABCD-E/16/07
DOI: http://doi.acm.org/10.1145/9999997.9999999

tration.
**Initial Segment based on Planar Fitting**
**Block Based Feature Extraction and Clustering**
The result of Clustering:

$$P(B_{mj} \in C_n)$$

**Soft Correspondence Initialization**
Then the $\alpha$ is initialized as:

$$\alpha_{ijk} = P(B_{mj} \in C_n)$$

on the condition that:

$$v_{ij} \in B_{mj} \wedge x_k \in O_n$$

## 5 Experiments and Discussion

### 5.1 Debugging The Smooth Step

**Bug Description:**
When the smooth step is added, the mixture of gaussian model won't expand to fit the input observations.
**Test Case Generation:**
In order to debug the problem, I generated a set of six synthetic point clouds. For the purpose of debugging, I deliberately made sure that the first 2657 points belonging to table, the following 2028 points belonging to chair, the last 3286 points belonging to teddy. The Test Cases are shown in Figure 1.

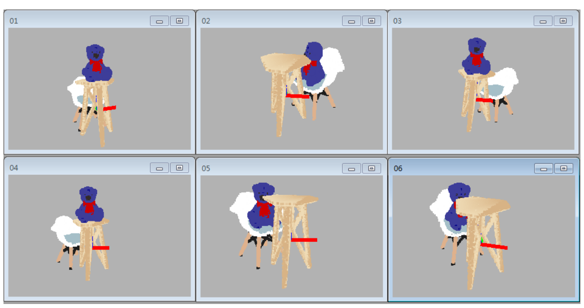


**Figure 1:** *The Synthetic Data for Test:they are composed of three objects (teddy table and chair) with different rigid motion*

**The Example of $\alpha$:**
The $\alpha$ are caculated as

$$\alpha_{ijk} = p_n p_k N(\phi_n(v_{ij})|x_k, \Sigma_k)$$

The example $\alpha$ with no smooth:

### 5.2 Current Result

As shown in Figure 2

### 5.3 Initialization Experiments

## Acknowledgements

To Robert, for all the bagels.

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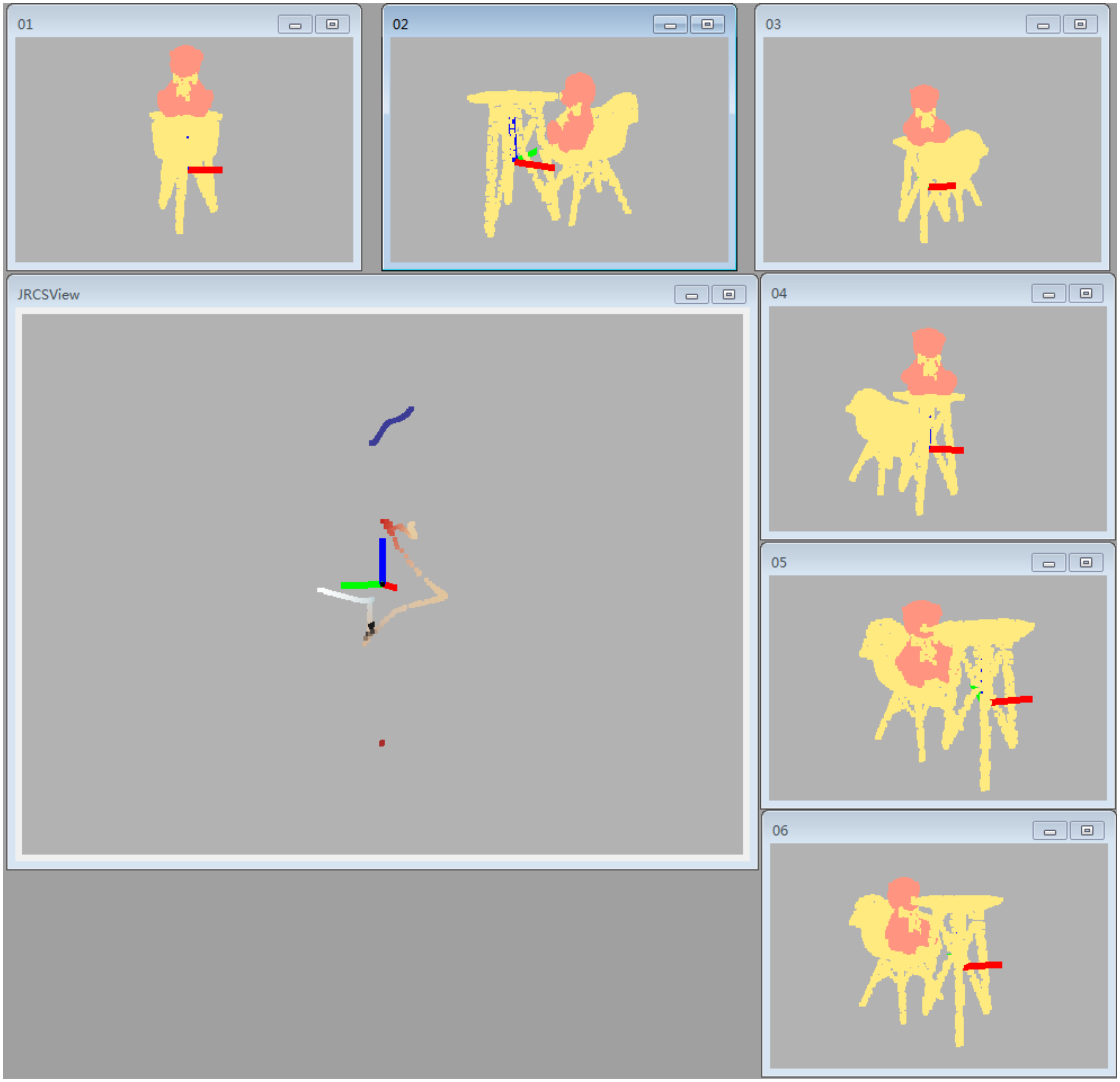


**Figure 2:** *Current Result*

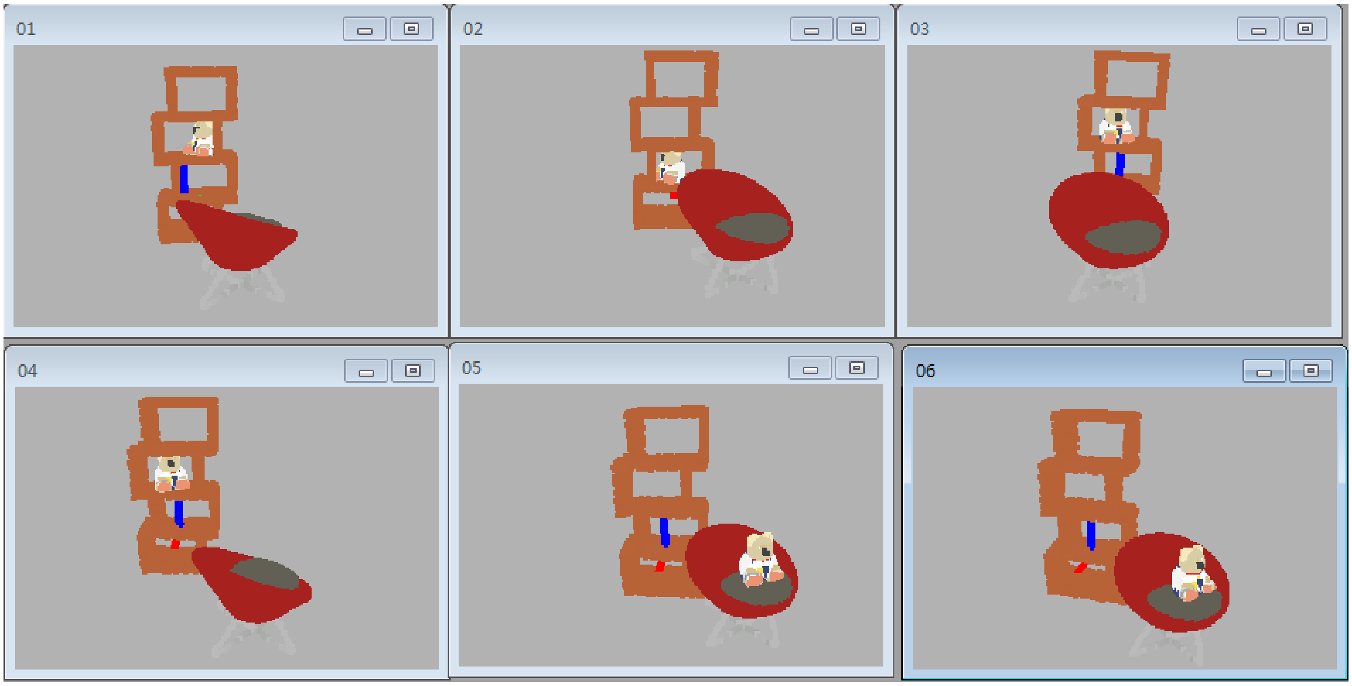


**Figure 3:** *Input for Initialization Experiments*

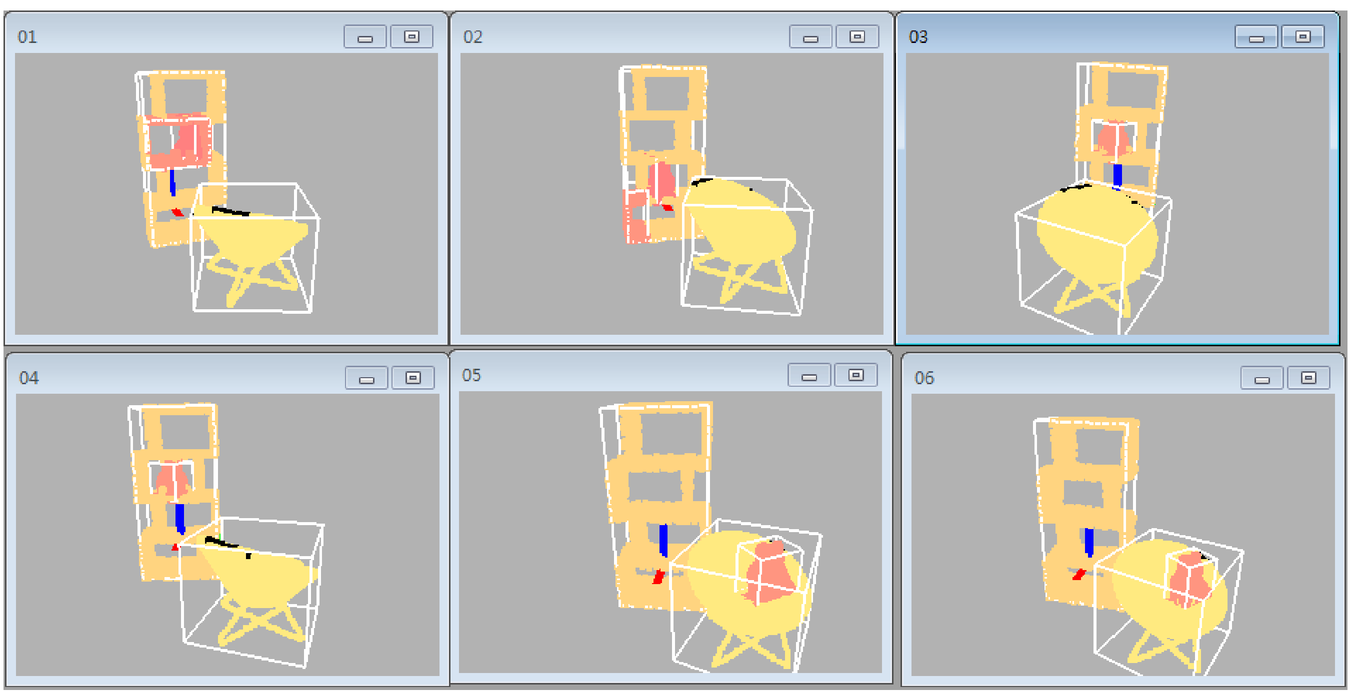


**Figure 4:** *Segmentation for Initialization Experiments*

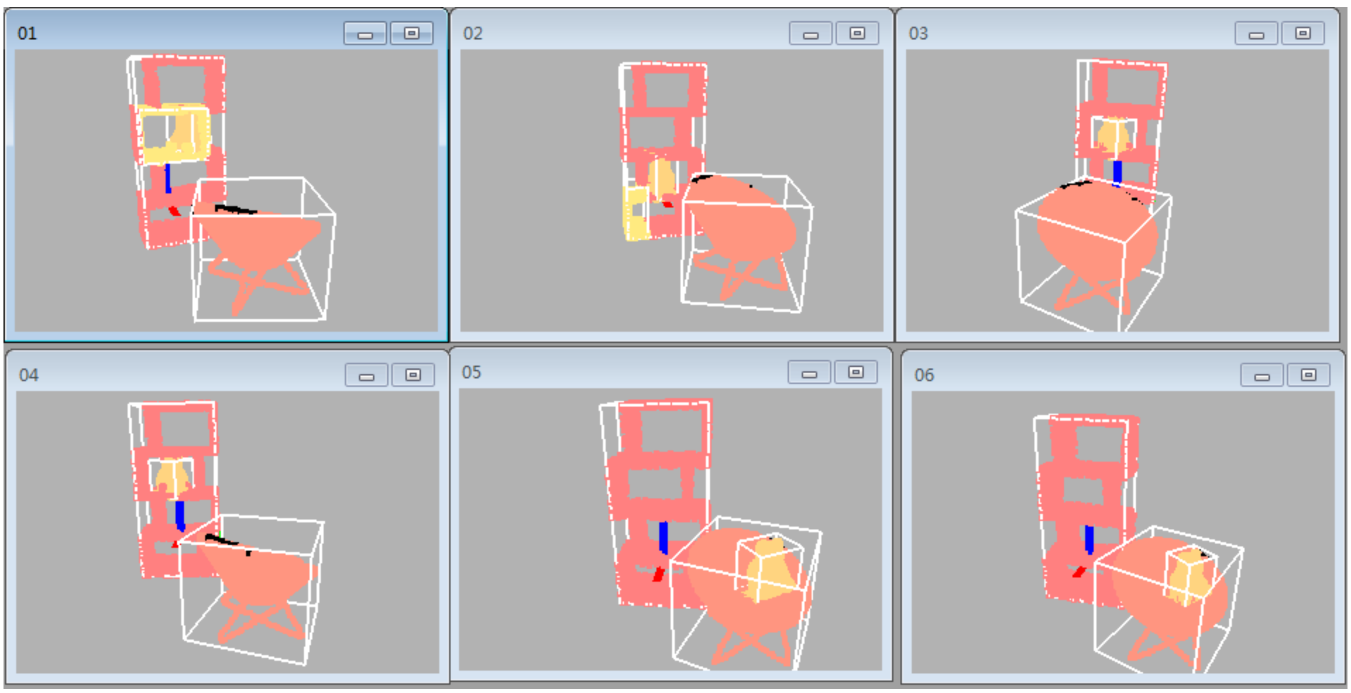


**Figure 5:** *Clustering for Initialization Experiments*