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

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Abstract

Keywords: Co-segmantion, Joint Registration

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

1 Introduction

In many researches and applications of indoor scenes the data of segmented and even annotated 3D indoor scenes are required as either data base or training data (e.g.[Nan et al. 2012][Dema and Sari-Sarraf 2012][Fisher et al. 2012][Chen et al. 2014][Fisher et al. 2015]).

One way to build such data base is to interactively compose scenes from 3D shape models resulting in scenes with object segmentation and annotation naturally available, or to mannually segment and annotate existing scenes. This procedure can be tedious and time consuming, despite the efforts to improve the interaction experience(e.g.[Merrell et al. 2011][Xu et al. 2013]).

Another way is to automatically generate scenes from 3D shape models according to the input RGB or RGB-D images(e.g.[Liu et al. 2015][Chen et al. 2014]). In such methods, a retrievial procedure is usually needed and inevitablely limit the result to a certain set of 3D models despite the actual 3D model in the input images.

We prefer a approach that helps us build such data set directly from the captured data. One of the major gap between the required data set and available scene capturing framework(e.g.[Izadi et al. 2011]) is the general object level segmentation. We want to stress that a general object level segmentation problem should not be treated as an equivalence of multilabel classification problem since it is not limited to a certain set of objects. For 3D data, [Jia et al. 2015] used some simplified physical prior knowledge (i.e. the block based stability) to help acheiving the general object segmentation, while the work of [Xu et al. 2015] proposes a practical and rather complete framework to close the gap between the required data set and available scene capturing method. One of the observation in [Xu et al. 2015] is that the motion consistency of rigid object can serve as a strong evidence of general objectness. To exploit this fact, they employ a robot to do proactive push and use the movement tracking to verify and iteratively improve their object level segmentation result. Our work presented in this paper is trying to exploit the same observation from a different approach.

We intend to use the motion consistency that is naturally revealed by human activities along the time. Down to this approach, we are facing the choice of scanning scheme. One way is to record the change of the scene along with the human activities, another is to arrange a daily or even a once every half day sweep to only record the result of human activities but avoid the instant of human motion. The main challenge brought in by the second scheme is that we may not be able to solve the object correspondence by a local search due to the sparse sampling over time, but the very same challenge exists in the first scheme due to the exclusion caused by human bodies not to mention other additional process(e.g. tracking with severe oclussion) needed for human bodies. With the second scanning scheme, our original intention of building 3D scene data set from capturing naturally leads us to the problem of coupled joint registration and co-segmentation.

In this problem, registration and segmentaion are entangled in each other. On one hand the segmentation depends on the registration to connect the point clouds into series of rigid movement so that the object level segmentation can be done based on the motion consistency, on the other hand, the registration depends on the segmentation to break the problem into a series of rigid joint registration instead of a joint registration with non-coherent point drift(A pair of points is close to each other in one point set but their correspondent pair of points in another point set is far from each other, in other words, the point drift of this pair is non-coherent. This happens when this pair of points actually belong to different objects.)

To model the problem, we employ a group of gaussian mixture models and each of these gaussian mixture models represents a potential objects. This modeling handles the entanglement of registration and segmentation in the way that

2 Related Work

2.1 Point Set Registration with GMM Representation

[Chui and Rangarajan 2000]
[Myronenko and Song 2010]
[Jian and Vemuri 2011]
Our work is most related to [Evangelidis et al. 2014]. We actually extend the formulation of [Evangelidis et al. 2014] to simultaneously handle joint registration and co-segmentation.

2.2 Functional Mapping

The coupled joint registration and co-segmentation problem comes with a latent 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 [Maron et al. 2016], 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 **??** 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:

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

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:

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

in which:

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

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.
Σ_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:

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

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

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 registration. **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 α is initialized as:

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

on the condition that:

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

Algorithm 1 Joint Registration and Co-segmentation (JRCS)

Input:
$\{V_m\}$:Observed point clouds
$\{\alpha_{mik}^0\}$:Initial posterior probabilities
Output:
Θ^q:Final parameter set

1. $q \leftarrow 0$
2. **repeat**
3. CM-step-a: Use α_{mik}^q, x_k^{q-1} to estimate $\{R_{mn}^q\}$ and $\{t_{mn}^q\}$
4. CM-step-b: Use α_{mik}^q, $\{R_{mn}^q\}$ and $\{t_{mn}^q\}$ to estimate the Gaussian centers x_k^q
5. CM-step-c: Use α_{mik}^q, $\{R_{mn}^q\}$ and $\{t_{mn}^q\}$ to estimate the covariances Σ_k^q
6. CM-step-d: Use α_{mik}^q to estimate the priors p_k^q
7. E-step: Use Θ^{q-1} to estimate posterior probabilities. $\alpha_{mik}^q = P(z_{mi}|v_{mi}; \Theta^{q-1})$
8. $q \leftarrow q + 1$
9. **until** Convergence
10. **return** Θ^q

5 Experiments and Discussion

5.1 Debugging The Smooth Step

5.2 Current Result

5.3 Initialization Experiments

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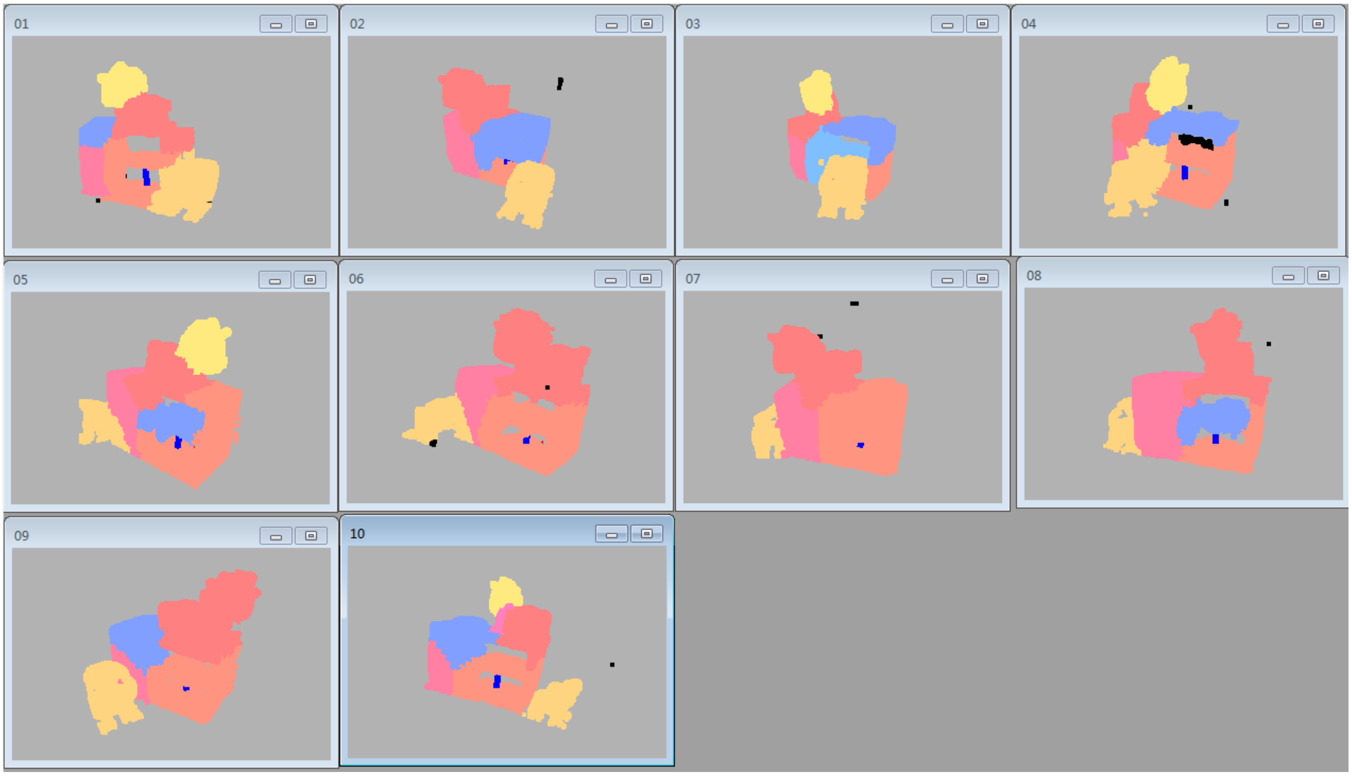

Figure 1: *Segments and mannully clustered result*

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