

Spatio-Temporal reconstruction of Rigid objects from multiple cameras

Abstract

Multi camera based understanding of dynamic scenes from unsynchronized images is a challenging problem in reconstruction. We propose a solution to the problem of 3D reconstruction of multiple moving rigid objects from unsynchronized multiple cameras. Most of the reconstruction pipelines leverage reconstruction using reprojection error of features, we propose a novel semantic features pipeline and object based feature tracking for reconstruction of dynamic objects. We leverage multiple rigid object constraints in a bundle adjustment framework to improve the reconstruction.

1. INTRODUCTION

We propose dynamic reconstruction of rigid objects from multiple unsynchronized and in the wild captured cameras. The main contributions of the algorithm are:

1. Novel instance keypoint detection pipeline for reconstruction of moving objects.
2. Constraint Bundle adjustment for reconstruction of dynamic rigid moving objects from viewed from multiple cameras.
3. End-to-End dense reconstruction of rigid objects from multiple unsynchronized cameras.

2. METHOD

We Follow the basic pipeline of reconstruction i.e. feature detection and tracking, correspondence of the keypoint across views and then bundle adjustment for accurate reconstruction of the 3d points. In each of the segments of the pipeline we incorporate geometric and semantic information of the objects for better reconstruction. We propose instance keypoint segmentation for better feature detection of important points on the rigid object. We first formulate the problem statement for the problem. Lets assume N video cameras observing P 3d points over time $X^p(t)$ and their 2D projection $x_n^p(f)$ on camera p and frame f is given as:

$$\begin{bmatrix} x_n^p(f) \\ 1 \end{bmatrix} = K_n(f)[R_n(f)|T_n(f)] \begin{bmatrix} X_n(f) \\ 1 \end{bmatrix}$$

where $K_n(f)$ is the intrinsic camera matrix, $R_n(f)$ and $T_n(f)$ are the relative camera rotation and translation, respectively. We denote this transformations $x_c^n(f) = P_n(f, X^n(t))$

2.1. Instance Aware Keypoint detection

Given a images with multiple moving objects. The amount of objects which can move can be sorted into a small set of categories like cars and humans. We propose a instance keypoint detection on these categories for improving the reconstruction of these objects. We leverage deep learning framework for fast and accurate detection of semantic features in images. We pass the input image through a detection pipeline and each detected bounding box is passed through a object specific keypoint detection pipeline for computation of semantic features in an image.

2.2. Object aware keypoint tracking

Tracking of keypoints has generally been considered as a search problem over the image space for features of similar shape in adjacent images. Semantic aware tracking correspondences to tracking of the important parts using the knowledge of the object i.e. the keypoints on the wheels are tracked by finding the correspondences of cars overtime. This gives a better tracks of the keypoints and longer correspondences compared to the feature based tracking methods.

2.3. Correspondence across views

We currently have tracks of objects and their respective keypoints in each individual video for all videos of the scene. For accurate reconstruction of objects from multiple views we need to find correspondences across views. We propose a object specific bundle adjustment for finding correspondences across views. Lets assume we have h object proposals in N videos at time t . The problem of correspondence is finding g , where $g \subset h$ object bounding boxes which belong to the same object. Since there is a spatial constraint on the bounding boxes over multiple views, Fig 1 shows the bundle adjustment we use to find correspondences across views. We propose a ransac based methodology

for finding correspondences across views and minimize the following reprojection error:

$$E_r = \sum_{n=1}^N \sum_{p=1}^P \sum_{f=1}^{F_n} V_n^p(f) \|P_n(f, X^p(t)) - x_n^p(f)\|^2 \quad (1)$$

where E_r is the image reprojection error, $V_n^p(f)$ is a binary indicator of the visibility of the keypoint. We add additional constraints like symmetry and the length of different joints of the object for accurate fitting of the rigid object in 3D. A joint in 3d can be defined as the difference of the 3D points between the centers of the joint. We define a joint as $J(p1, p2) = X^{p1}(t) - X^{p2}(t)$ where $p1$ and $p2$ correspond to different parts of the rigid object which are linked.

$$E_l = \sum_{r=1}^R \|J(r) - E(J(r))\|^2 \quad (2)$$

where $E(J(r))$ is the mean length of joint r . We model the symmetry constraint in the bundle adjustment for better reconstruction of rigid objects.

$$E_j = \sum_{q=1}^Q \|J(q) - J(S(q))\|^2 \quad (3)$$

where $S(q)$ gives the corresponding symmetric joint of q i.e. if q is the joint connecting the left wheels of a car $S(q)$ is the joint connecting the right wheels of the car.

2.4. Spatio-Temporal Bundle Adjustment

Once we have the correspondences across cameras and views, We get the fit a motion model based rigid object over time. The formulation is given by:

$$E_{st} = \sum_{t=1}^T w_r E_r + w_j E_j + w_l E_l + w_m E_m \quad (4)$$

where w represents the weights of each term in the bundle adjustment. E_m is defined as the motion prior over the trajectory of the points.

$$E_m = \sum_{p=1}^P \sum_{i=1}^{T^n-1} \left\| \frac{X^p(t^{i+1}) - X^p(t^i)}{t^{i+1} - t^i} \right\|^2 (t^{i+1} - t^i) \quad (5)$$

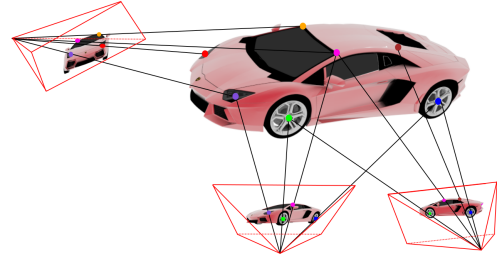


Figure 1. The picture depicts the projection of 3D keypoints of car onto their respective videos