Structure from Motion System in Modern Browser

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Abstract

This thesis aims at constructing a 3D reconstruction system on mordern web platfrom. We propose a 3D reconstruction pipleline and its integration/optimization for the web platform.

1 Introduction

The title Structure from Motion System in Modern Browser implies two key aspects, *3D Reconstruction* and *Web Platform*, and both sides have great potential.

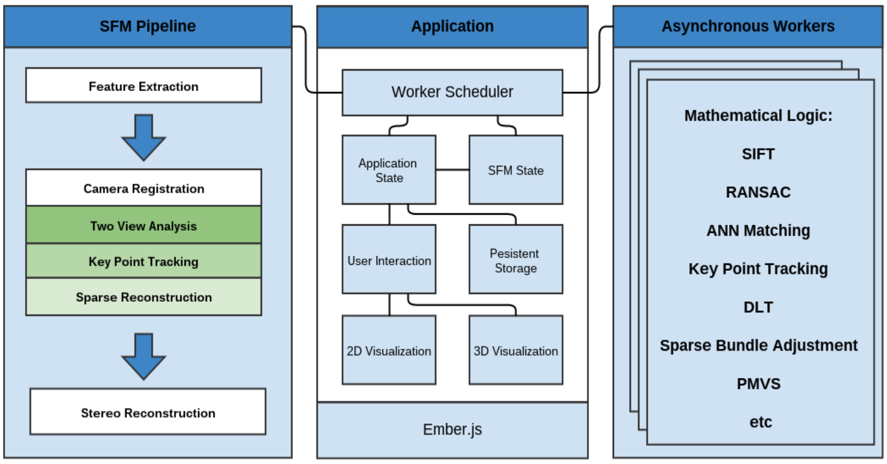
On one hand, structure from motion has always been a critical part of computer vision. In resent years, structure from motion has became increasingly relavent because of the rise of consumer drones and VR. Reconstruct 3D scene directly from regular photos taken by digital camera instead of specialized equipments can dramatically decreased the requirements for this important task, and open up the door to potentially unlimited resource for 3D reconstruction.

On the browser side, with increasing amount of advanced features like WebGL, WebWorkers, TypedArray, web platform can now host graphic/computation insense complex applications, which made implementing an SFM system possible. With the intrinsic advantage of the web platform, application build upon it will be both sophisticated and out-reaching.

On the other hand, modern browser as a platform is gaining its popularity. It has became increasingly powerful over the years both in functionality and performance. Several novel features of the modern browser has made implemeting an SFM system possible. First is the WebWorkers. Javascript is a single threaded language, with WebWorker, parallel computing with clent-side javascript became possible. Another one is WebGL, which is the openGL interface for the web. It made the rendering of 3D models. Last but not the least, Indexed DB is also a very important element. It implements a light weight object storage database, enables versitle persistent storage inside browser.

This project attempt to construct a 3D reconstruction system on modern web platform, take advantage of the advanced capability of modern browser, its enormous install base and its cross platform nature, make 3D reconstruction avaliable everywhere.

2 Overview



. Framework of WebSFM

3 Mathematical Context

3.1 Coordinate System

Points in the SfM pipline have multiple cooridates according to different frames of reference.

- `Image Coordinate` – x
- `Camera Coordinate` – X_{cam}
- `World Coordinate` – X

Transition between these coordiate systems are accomplished by the use of homogenous coordinate and transition matrices.

- `Rotation Matrix(R) and Translation Vector(t)` – $X_{\text{cam}} = \begin{pmatrix} R & t \\ 0 & 1 \end{pmatrix} \cdot X$
- `Calibration Matrix(K)` – $x = K \cdot [I, 0] \cdot X_{\text{cam}}$
- `Projection Matrix(P)` – $x = PX = K \cdot [R, t] \cdot X$

3.2 Camera Model

Camera model have multiple forms

- `Standard Linear Projective Camera Model (Undistroted)`
  - `Rotation Matrix (R)`
  - `Translation Vector (t)`
  - `Calibration Matrix (K)`
  - `Projection Matrix (P=K[R,t])`
- `Parameterized Full Camera (with distortion) -` 11 variables
  - `Euler Angles (r) -` 3 variables
  - `Translation Vector (t) -` 3 variables
  - `Principal Point (px, py) -` 2 variables
  - `Focal Length (f) -` 1 variable
  - `Radial Distortion (k1, k2) -` 2 variables

Parameterized full camera with ditortion is only used during camera registration. Distortion is ignored before camera registration; after registration cameras are undistorted.

4 Pipeline

Structure from motion pipline of WebSFM is largely based on Bundler.

First generate SIFT features for each image (details in 4.1), then perform robust two view analysis on each pair of images (details in 4.2).

A track represents a point in the 3D space, it has one or no view on an image, we will find tracks by merging two view matches to a graph and traversing the match graph, tracks that have more than one view on a single image is excluded as an obvious outlier.

Tracks are then used to initiate camera registration. We first choose a pair of camera to initiate. After initiation, incremental recovery is performed (details in 4.3), and sparse reconstruction is obtained.

Currently WebSFM does not handle reconstruction beyoned sparse. PMVS/CMVS [5] can generate dense oriented point cloud, which can then be used to recover surface polygon using Pission surface reconstruction.

4.1 SIFT (Scale Invariant Feature Transform)

Lowe's SIFT[1] is our choice of feature extractor. SIFT features can be detected and matched regardless of its scale, orientation or lighting, following is an overview of SIFT algorithm:

Algorithm SIFT

```
features := empty array
for each octave:
    scales space := progressive blur the base image of current octave
    dog space := subtract adjacent scales in scale space
    for each extrema in dog space:
        if principal curvature of extrema is too big or negative: break
        subpixel := interpolate extrema position in dog space, at (x,y,scale)
        orientations := domiant orientations of gradient histagram in sacle space
        for each orientation in orientations:
            descriptor := gradient distribution histagram in scale space
            features += (octave,subpixel,orientation,descriptor)
        end for
    end for
end for
```

Octave space start at -1 or 0, choose -1 if image is too small. In each octave, we will scan 3 DoG layers, which requires 5 layers in DoG space, and 6 layers in Guassian space. When bluring the image, larger sigma means larger kernel size, then directly leads to more time consumption, so blur is done progressively to keep sigma relatively small. We use default descriptor size stated in lowe's original paper, $4 \times 4 \times 8$ histagram and 128 dimensional Uint8 vector.

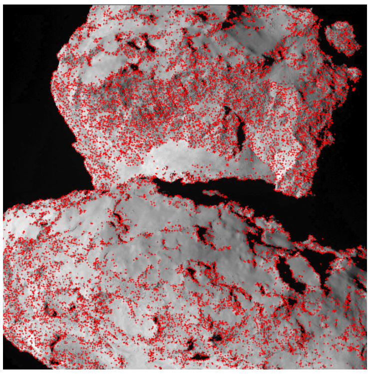


Figure 1.

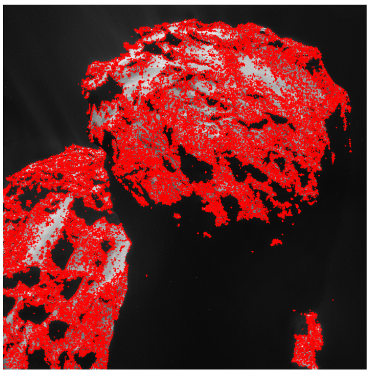


Figure 2.

4.2 Robust Two-View Analysis

the objective of *Robust Two-View Analysis* is to find robust two view matches and accurate epipolar geometry i.e. fundamental matrix from sift features of two images. we complish that by perform ANN [4] feature matching on SIFT features, and use RANSAC with eight-point-algorithm to make the dataset robust, then obtain an accurate estimation of fundamental matrix from inliers.

ANN search

Two-view constrains:

- `Fundamental Matrix(F)` – $x_1^T F x_2 = 0$
- `Essential Matrix(E)` – $X_{\mathrm{cam1}}^T E X_{\mathrm{cam2}} = 0$

Fundamental matrix is used for un-calibrated cameras, essential matrix is used for calibrated cameras, their relation is $F = K_1^T E K_2$.

To select the desirable tracks, first match features for each pair of images. Instead using a threshold of the euclidean distance of two descriptor to indicate a match, we use a nearest neighbor strategy. When comparing two inages, for each feature in image 1, we find the 1st and 2nd nearest feature in image 2 and compare the ratio of the euclidean distance, if less then the ratio threshold, then accept as a match, which means it's a match and the only match in this image. then, use view constrains to filter the matches. for each image pair, use two view constrain, fundamental matrx. use RANSAC to estimate the fundamental matrix and filter outlier matches.

To satisfy the second requirment, we construct image connectivity graph from all feature matches, tracks that contains multiple matches on a single image will be discarded. In this process, not only inconsistencies are filtered, we also merged two-view matches into a global image connectivity graph and global tracks, which can be used in next phase.

4.3 Incremental Sparse Reconstruction

After the sparse structure is initiated, incremental recovery is performed. It will recover new cameras from recovered tracks, and triangulate more tracks, mean while use *SBA* and *Robust SBA* minimize projection error and keep the sparse structure robust, following is an overview of the algorithm:

Algorithm Incremental Sparse Reconstruction

```
tracks := input
recovered cameras := initial sturcture
recovered tracks := initial structure
candidates := un-recovered cameras view at least 20 recovered tracks
while candidates avaliable
    selected := candidate view the most recovered tracks and those above 75 percentile
    new cameras := recover camera models of selected candidates using DLT
    recovered cameras += new cameras
    sparse bundle adjustment on new cameras and recovered tracks they observe
    new tracks := triangulate tracks at maxium view angle within recovered cameras
    recovered tracks += new tracks
    global robust sparse adjustment
    candidates := un-recovered cameras view at least 20 recovered tracks
end while
```

Recover new camera parameters is accomplished by obtain its projection matrix through DLT and then decompose it into `(R, t, K)`, which can then be paramterized and refined.

When triangulate new points, big view angle is required. Only triangulate if the maximum view angle within recoverd cameras is larger then a threshold.

Figure 3. result of sparse reconstruction

4.4 Sparse Bundle Adjustment (SBA)

The objective of *Sparse Bundle Adjustment (SBA)*[2] is to minimize projection error of a sparse reconstruction by perform non-linear approximation on camera paramters and 3D points. It is a modified implemention of *Levenberg-Marqurdt Algorithm* that take advantage of the sparse structure of muti-view geometry.

Sparse sturcture is exploited when calculating *Jacobian*, *damped Hessian* and $\boldsymbol{\delta}_p$. When solving

$$(H + d \cdot I) \cdot \boldsymbol{\delta}_p = \boldsymbol{\epsilon}$$

the damped Hessian can be splite into $\begin{pmatrix} A & B \\ B^T & V \end{pmatrix}$, where V is a block diagnal matrix, and equation can be solved using Shur's component.

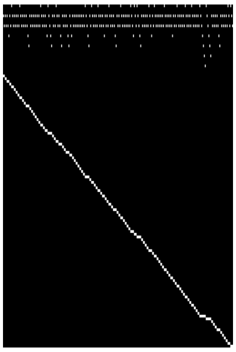


Figure 4. sparse jacobian matrix

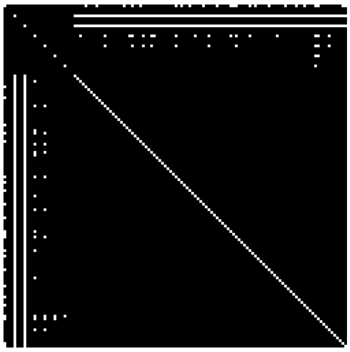


Figure 5. sparse damped hessian matrix

Robust SBA is SBA with outiler filter, it will refine the paramters and exclude outliers until no outliers can be found, following is an overview of its algorithm:

Algorithm Robust Sparse Bundle Adjustment

inliers := input tracks
cameras := input cameras
do
  sparse bundle adjustment on *cameras* and *inliers*
  for each $\texttt{camera}_{\texttt{vi}}$ in *cameras*:
    d_{80} := 80 percentile of reprojection error on $\texttt{camera}_{\texttt{vi}}$
    $\texttt{threshold}_{\texttt{vi}} := \mathrm{clamp}(d_{80}, 4, 16)$
    $\texttt{outliers}_{\texttt{vi}}$:= tracks with reprojection error larger then $\texttt{threshold}_{\texttt{vi}}$
  end for
  outliers := $\bigcup$ $\texttt{outliers}_{\texttt{vi}}$
  inliers := *inliers* - *outliers*
until *ouliers* is empty

5 Application Framework

5.1 Parallelization

structure from motion pipline contain large mount of independent calculations, which can be

We encapsulate computation intense logic into tasks, and put all tasks into a single script file **worker.js**, which can have more than one instance. Then **application.js** can instantiated it inside browser and uses WEBWORKER's event interface to call those tasks aynchronously. Task includes:

- SIFT task, take ImageData (as ArrayBuffer) and returns point buffer and vector buffer (as ArrayBuffer)
- Matcher task, take two camera shapes and two SIFT results, returns robust two view analysis
- Tracking task, takes SIFT point buffer of each image and all robust two-view analysis results, returns an array of tracks.
- Register task, takes tracks and fundamental matrics, returns a sparse point buffer and camera parameters

5.2 Data Model

Large amount of data flow through the pipeline,

We use a hierarchy of NDARRAY, TYPEDARRAY, and ARRAYBUFFER to handle large data, which uses ARRAYBUFFER as the underlying payload. For networking, it can be directly transfered through XMLHTTPREQUEST as a native response type, For storage, it's supported in all implementations of INDEXEDDB. For multi-threading, it is a TRANSFERABLEOBJECT for WEBWORKERS. Data are stored in its minimum form through TypedArray, no JSON or text involved, which also means no parsing required.

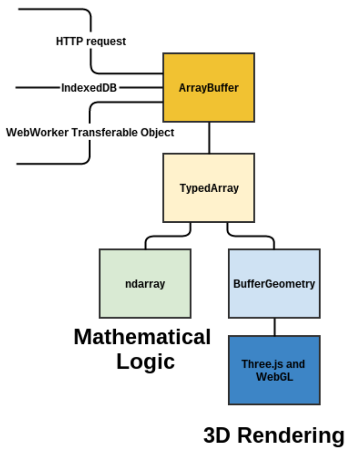


Figure. WebSFM data model

5.3 Demos

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