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.

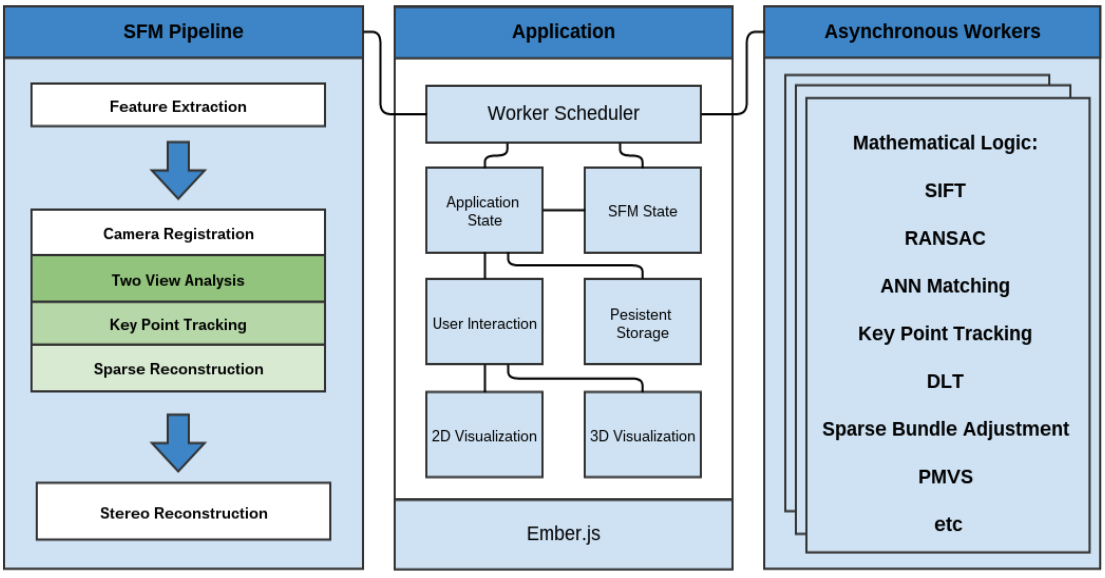
On one hand, structure from motion has always been a critical part of computer vision. In resent years, structure from motion has became increasingly relavent because of the rise of consumer drones and VR. Reconstruct 3D scene directly from regular photos taken by digital camera instead of specialized 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), robust two-view matches produced by this process can then be used to track key points.

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.

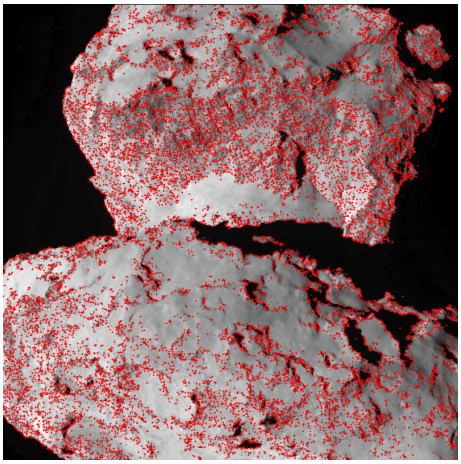


Figure 1.

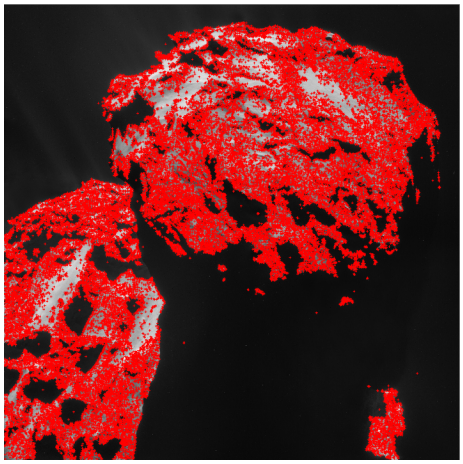


Figure 2.

4.2 Robust Two-View Analysis

The objective of *Robust Two-View Analysis* is to find robust two-view features matches and accurate epipolar geometry i.e. fundamental matrix estimation from SIFT features of two images.

We need to first obtain the *approximate nearest neighbor (ANN)*[4] of SIFT features. Instead using a threshold of the Euclidean distance of two descriptor to indicate a match, we use a priority queue to match feature, and use a threshold on the ratio of distance between the best match and the second match. We also use approximate nearest neighbor search rather than strict for performance

concern. Features also need to be the ANN of *each other* to be accepted as a match.

Then we use two-view epipolar constrain to stablelize the matches. Each pair of point coorespondence must satisfy $x_1^T F x_2 = 0$, where F is the fundamental matrix. We exploit this attribute by combine RANSC and *normalized eight point algorithm* to filter outliers, and then estimate the *fundamental matrix* by SVD on the inliers and non-liear approximation by LMA.

The result of *robust two-view analysis* can even be recoganized by naked eyes after visualization.

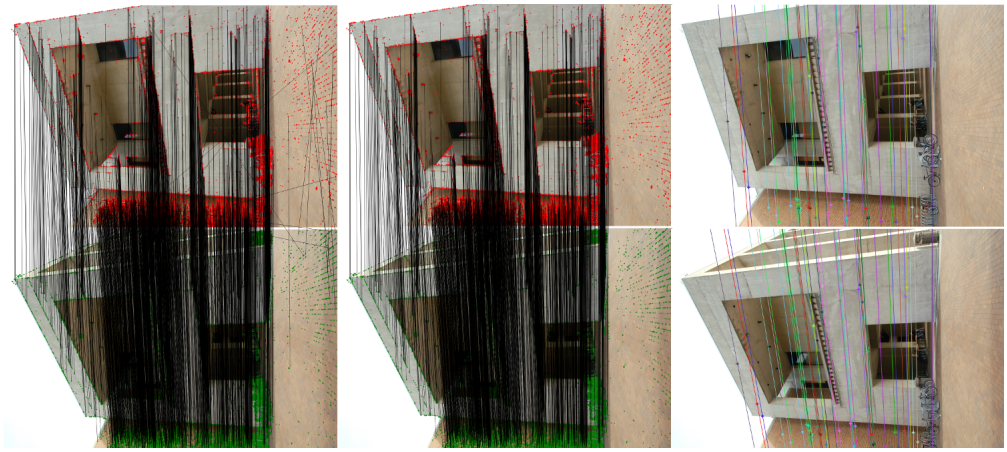


Figure 3. raw matches, robust matches and epipolar lines

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.

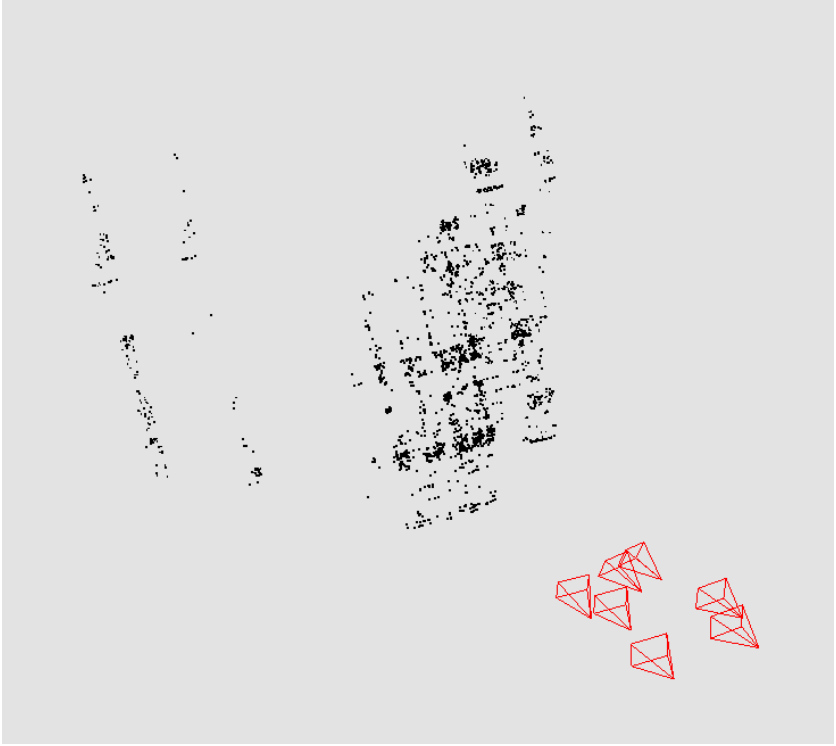


Figure 4. result of sparse reconstruction

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.

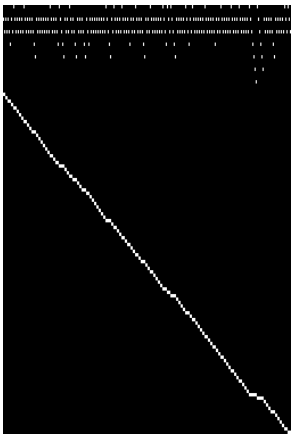


Figure 5. sparse jacobian matrix

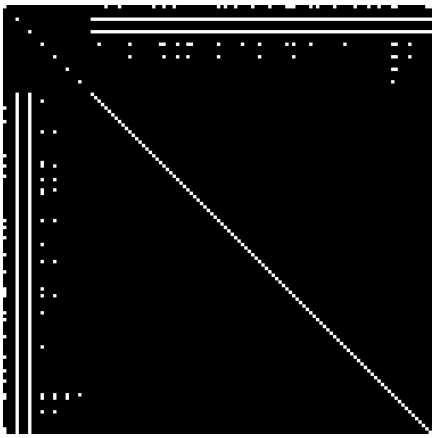


Figure 6. sparse damped hessian matrix

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 $\texttt{camera}_{\texttt{vi}}$
    $\texttt{threshold}_{\texttt{vi}} := \text{clamp}(d_{80}, 4, 16)$
    $\texttt{outliers}_{\texttt{vi}}$:= 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, how to handle large data is especially critical inside browser.

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.

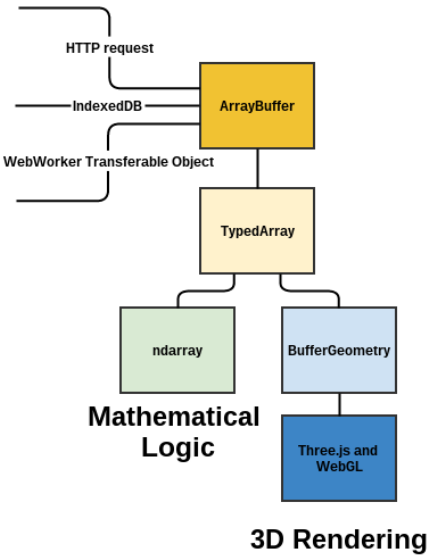


Figure. WebSFM data model

Following are the specifics of how data is represented as ARRAYBUFFER:

- SIFT features are stored in two seperate parts, *points* and *vectors*. *Points* is a $4 \times l$ ndarray with an underlying FLOAT32 typed array as buffer, which stores *row*, *column*, *orientation*, *scale* of each feature point. *Vectors* is a $128 \times l$ ndarray with an underlying UINT8 typed array as buffer, which stores 128 dimensional descriptor of the cooresponding feature point in the *points* buffer. When matching features, only the *vectors* buffer is used, and when visualizing or tracking key points, only the *points* buffer is used.

- Surfels, both dense and sparse, is represented as two parts, *points* and *colors*. *Points* is a $3 \times l$ ndarray with an underlying Float32 typed array as buffer, which stored the patch center coordinate. *Colors* is a $3 \times l$ ndarray with an underlying Uint8 typed array as buffer, which stores RGB color of the cooresponding patch in the *points* buffer.

Other data such as *camera paramters*, *feature matches* are insignificant in comparasion, so are directly stored as JSON objects.

To exam this approach, we take surfel model generated by PMVS which contains 450,000 patches. It costs 24.2MB in its original text form. this approach, data is stored in its minimum form, *points* and *colors* have combined size of 6.8MB.

5.3 Demos

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