Image Stitching - a Brief Review

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Overview

Image Stitching Basics

Motivation

Image Stitching and Geo-correction

- Large scale ($\sim 7000 - 10000$)
- Low overlap (30% horizontally, 9% vertically)
- Geo-Referencing is important
- Commercial softwares break

Image Stitching

Image Alignment and Stitching: Process of finding geometric relation between overlapping images and generating a final image with larger field of view by mosaicing and blending the individual images into a specific frame.

- Image acquisition platforms
  - Hand-held cameras
  - Satelite Imagery
  - Aerial Imagery
  - Drone Imagery
  - Ground Vehicles
- Applications
  - Remove Sensing
  - Agriculture management
  - Disaster management
  - Panorama generation

Image Stitching Components

- Keypoint/Feature Detection
- Keypoint/Feature Correspondence Calculation (Matching)
- Transformation Estimation
  - Intensity based
  - Feature based
- Image Alignment
- Image Warping and Stitching
- Image Blending and Seamless Stitching

Keypoint/Feature Detection

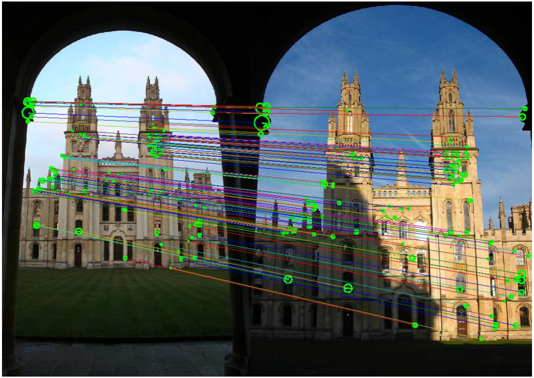
Visually important points on the image.

- HARRIS
- SIFT
- SURF

Keypoint/Feature Matching

Finding Correspondences

- KNN
- Voronoi diagrams + Cross correlation



Transformation Estimation

Geometric relation of images depends on many things:

- Homography (Perspective Projection)
  - Scene is planar (or far away)
  - Camera rotating around optical center
- Similarity
  - Leveled camera (no tilting)
- Translation

Transformation Estimation

- Using correspondences to estimate transformation
  - Simple LSQ
- Be robust to outliers
  - RANSAC
  - BAY-SAC

Transformation Estimation

More complex warps and transformations

- Address the non-planar scenes
- Parallax effects

Warps:

- As-projective-as-possible
- Shape-preserving half-projective

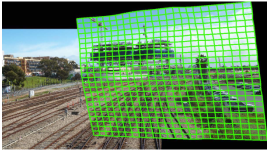
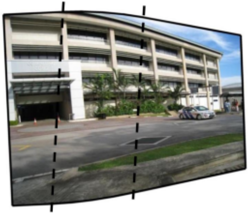




Image Alignment

Major challenge in stitching multiple images: Accumulation of minor errors $\rightarrow$ Drift. Can be solved by:

- Global alignment (such as bundle adjustment)
- Incorporating prior knowledge

Image Blending and Seamless Stitching

Generate visually pleasant mosaics:

- Seamless Stitching
  - Graph cut method
- Blending techniques
  - Linear averaging
  - Multi-band blending

Multiple Image Alignment

- Image stitching is a difficult field to be innovative in.
- Noticeable number of papers only make the previous methods fancier (my point of view).

Multiple Image Alignment

Already discussed:

- Automatic panoramic image stitching using invariant features (Brown and Lowe)
- MGRAPH: A Multigraph Homography Method to Generate Incremental Mosaics in Real-Time From UAV Swarms

In this presentation:

- Image mosaicing using sequential bundle adjustment
- A Novel Adjustment Model for Mosaicking Low-Overlap Sweeping Images
- Natural Image Stitching with the Global Similarity Prior
- Robust UAV Thermal Infrared Remote Sensing Images Stitching Via Overlap-Prior-Based Global Similarity Prior Model

Sequential Bundle Adjustment

Image mosaicing using sequential bundle adjustment

- Relatively an old paper.
- First paper that suggests using bundle adjustment to do image stitching (not 3D reconstruction).
- Initial and approximate orientation of the images need to be given manually.
- They show how to do bundle adjustment using points as well as lines as features.
- Key point or line locations are found by using corner detection and Hough transform respectively.
- RANSAC and initial homographies used to find correspondences.
- Variable State Dimension Filter (VSDF) is used to solve bundle adjustment.

Sequential Bundle Adjustment

- Bundle adjustment

$$f(x) = \frac{1}{2}\sum_i \Delta Z_i(X)^\top W_i \Delta Z_i(X)$$

$$\Delta Z_i(X) = \underline{Z}_i - Z_i(X)$$

- $Z_i = Z_i(X)$: predicted value of the feature i corresponding to the observation from parameters X.
- $\underline{Z}_i$: observed value of feature i.
- W_i: some weights.
- Solve the optimization formula

Sequential Bundle Adjustment

Variable State Dimension Filter (VSDF)

- Uses Levenberg Marquardt algorithm
- Updates the state vector iteratively

Mosaicking of Low-Overlap Images

A Novel Adjustment Model for Mosaicking Low-Overlap Sweeping Images

- This paper makes the best use of available prior knowledge.
- Works on UAV images.
- Stitching error source:
  - Camera parameters
  - Exterior orientation of the UAV
  - Projection plane in the object space
- Parameters are separated and a new error model is defined based on these error groups.
- Projection is defined by using the lat, lon, orientation(compass), pitch, yaw, and role.
- Optimization function using this error model is minimized.

Mosaicking of Low-Overlap Images

Projection is defined as:

$$v = H_e P V \tag{1}$$

- Inputs/known parameters:
  - v is the image point
  - P is the projective matrix. (calculated using the given camera parameters and exterior orientation parameters)
- Outputs/Unknown parameters:
  - H_e is the error homograph (error model)
  - V is the 3D scene point

Mosaicking of Low-Overlap Images

Error model: built as a homograph

$$H_e = (H_{e3} H_{e2} H_{e1})^{-1} \tag{2}$$

- H_{e1}: Camera parameter error. Scale and translation.
- H_{e2}: Projection plane error. (?)
- H_{e3}: Exterior Orientation Error. Accounts for the error in GPS, compass information and tilts (pitch, yaw and role).

Optimization is done by an approach similar to that of bundle adjustment (nonlinear least squares).

Global Similarity Prior Model

Natural Image Stitching with the Global Similarity Prior

- The proposed method is built the as-projective-as-possible paper.
- They use a mesh deformation approach to align, warp and stitch images.
- An optimization function made up of global and local alignment terms is defined and minimized to find the alignment and warping parameters.

Global Similarity Prior Model

Steps:

- SIFT features are detected. APAP is used to define the grid and locally align the overlapping images.
- The warped mesh from APAP is considered. The vertexes of this mesh are the new matched points which are used in this method.
- An energy function is defined which is consists of the following components:
  - Alignment Term: Ψ_a
  - Local Similarity Term: Ψ_l
  - Global Similarity Term: Ψ_g

Global Similarity Prior Model

Alignment Term:

- Ensures the alignment quality after deformation between the images.
- Equation:

$$\Psi_a(V) = \sum_{i=1}^{N} \sum_{(i,j)\in J} \sum_{p_k^{ij}\in M^{ij}} ||\tilde{\nu}(p_k^{ij}) - \tilde{\nu}(\Phi(p_k^{ij}))||^2 \tag{3}$$

- V is the list of vertexes of the mesh
- J is the list of overlapping images
- M is the list of all matched points between i,j
- $\tilde{\nu}$ expresses points position as a linear combination of four vertex positions that surround the keypoint.
- Φ returns the correspondence for a given keypoint.

Global Similarity Prior Model

Local Similarity Term:

- Locally avoids distortion on non-overlapping regions of the images.
- Ensure that each quad undergoes a similarity transform.
- Equation:

$$\Psi_l(V) = \sum_{i=1}^{N} \sum_{(j,k)\in E_i} ||(\tilde{\nu}_k^i - \tilde{\nu}_j^i) - S_{jk}^i(\nu_k^i - \nu_j^i)||^2 \tag{4}$$

- ν_k^i is the location of an original vertex k in image i.
- $\tilde{\nu}_k^i$ is the position of the vertex after deformation (parameter).
- S_{jk}^i is a similarity transformation for each edge. The parameters of this are expressed as linear combination of the vertexes.

Global Similarity Prior Model

Global Similarity Term:

- Preserves the naturalness of the stitched image.
- Ensure that each image undergoes a similarity transform.
- Equation:

$$\Psi_g(V) = \sum_{i=1}^{N} \sum_{e_j^i \in E_i} w(e_j^i)^2[(c(e_j^i) - s_i cos\theta_i)^2 + (s(e_j^i) - s_i sin\theta_i)^2] \quad (5$$

- e_j^i is an edge in image i.
- w is a weight function that assigns more weight to the edges that are far from the overlapped region.
- The rotation and scale parameters are estimated using the initial homographies from APAP (decomposition).

Global Similarity Prior Model

They proposed different methods for finding the best rotation for the final stitched image (naturalness).
The final optimization function is:

$$\tilde{V} = \arg\min_{\tilde{V}} \Psi_a(V) + \lambda_l \Psi_l(V) + \Psi_g(V) \tag{6}$$

They use a sparse linear solver to solve this optimization function.

Thermal Image Stitching using GSP

Robust UAV Thermal Infrared Remote Sensing Images Stitching Via Overlap-Prior-Based Global Similarity Prior Model

- Very similar to the previous paper.
- It is used on Thermal IR images.
- Probability of outliers is higher than RGB.
- Simply weight the GSP formula based on the overlap ratio of the images.

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Thank you for your attention

I will post the slides to my homepage at
`http://vision.cs.arizona.edu/ariyanzarei/`