

Analysis of Feature Point Distributions for Fast Image Mosaicking Algorithms

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Introduction

❖ Composition of image mosaics

- Fast image mosaicking algorithms are usually based on feature-based methods processing sparse sets of interest points.
- Distinctive image features are extracted and matched using similarity measurements.
- Many different feature detectors, showing robust matching, high repeatability, and precise alignment, have been proposed: SIFT, SURF, GLOH, MOPs, ...

❖ Problem:

Despite of high detector performance, feature point clusters with non-uniform spatial distribution, resulting from local contrast variability, lead to large global image registration errors.

- Medical application:** Endoscopic images of the internal urinary bladder wall show often only sparse located structures with high contrast, like vasculature or lesions.

❖ Image mosaicking algorithms can only process a limited number of feature points in real-time.

➔ Detector must distribute sparse data set of feature points uniformly across whole image to ensure low registration error.

➔ We analyzed different feature distribution algorithms and evaluated their average image registration errors.

Mosaicking Algorithm

❖ Image pairs of video sequence are sequentially stitched and blended to compose panoramic overview images [1],[2].

❖ Feature Detection:

Speeded Up Robust Features (SURF) [3] are extracted. Feature strength is calculated by

$$\det(\mathcal{H}) = \left\| \begin{bmatrix} L_{xx} & L_{xy} \\ L_{xy} & L_{yy} \end{bmatrix} \right\| \approx D_{xx}D_{yy} - (0.9 \cdot D_{xy})^2$$

with $L_{xx} = \text{Image} * \frac{\partial^2}{\partial x^2} \text{Gaussian}$,

using scalable box filters D_{xx}, D_{yy}, D_{xy} and integral images. 64-D feature descriptors \vec{d} are calculated using Haar wavelet filter.

❖ Matching and Registration:

Point correspondences are matched by least similarity and distinctiveness measurement:

$$\Delta \vec{d}_{ij} = \min_j \|\vec{d}_i - \vec{d}_j\|_2, \quad \frac{\Delta \vec{d}_{ij}}{\Delta \vec{d}_{ij}^{\text{2nd}}} < \tau$$

Estimation of image-to-image homography \mathbf{H} using affine transformation model:

$$\mathbf{H} = \begin{bmatrix} \mathbf{A} & \vec{t} \\ \vec{0}^T & 1 \end{bmatrix}, \quad \mathbf{A} = \begin{bmatrix} 1 & a & s_x & 0 \\ 0 & 1 & 0 & s_y \end{bmatrix} \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) \\ \sin(\alpha) & \cos(\alpha) \end{bmatrix}$$

False point correspondences $\vec{p}_i \leftrightarrow \vec{p}_j$ are rejected by RANSAC fitting algorithm and number of inliers is determined by threshold operation:

$$\|\vec{p}_i - \hat{\mathbf{H}} \cdot \vec{p}_j\|_2 < d$$

Evaluation

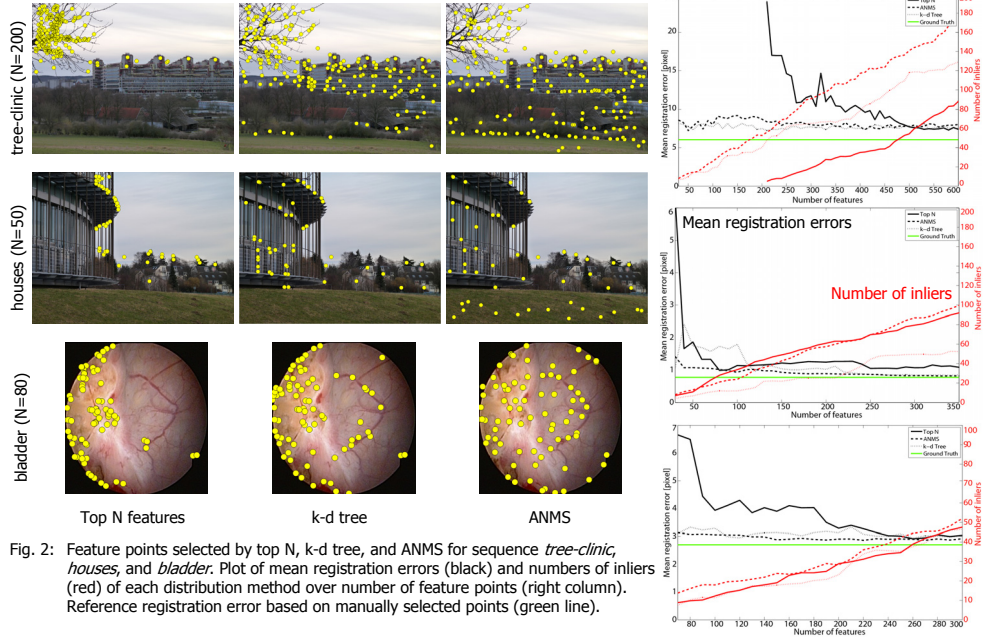


Fig. 2: Feature points selected by top N, k-d tree, and ANMS for sequence *tree-clinic*, *houses*, and *bladder*. Plot of mean registration errors (black) and numbers of inliers (red) of each distribution method over number of feature points (right column). Reference registration error based on manually selected points (green line).

Feature Selection

- Computational complexity of SURF detector increases linear with number of feature points.
- Real-time mosaicking algorithms desire a limited number of feature points.

➔ Separate feature point extraction into two steps:

- Detect locations and strengths of potential interest points.
- Select desired number of feature points.

❖ Top N Selection:

Select first N-th strongest feature points.

❖ Adaptive Non-Maximal Suppression [4]:

Select N feature points \vec{x}_i , which are local maxima and whose response values $f(\vec{x}_i)$ are greater than all of their neighbors within suppression radius: $r_i = \min_j \|\vec{x}_i - \vec{x}_j\|_2$, with $f(\vec{x}_i) < c \cdot f(\vec{x}_j)$

❖ K-d Tree Partitioning [5]:

Separate feature points into M rectangular image regions. In recursive manner cut each region with the current highest variance in two, until M cells are obtained. Select from each cell $\lfloor N/M \rfloor$ strongest features.

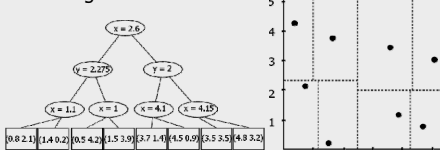


Fig. 1: 2-dim. k-d tree (right) and its cell partitions (left).

- Algorithm is extended to handle unbalanced k-d trees with any number of feature points.

Results

❖ Registration error is calculated by

$$e = \frac{1}{2} (\|\vec{p}_i - \hat{\mathbf{H}} \cdot \vec{p}_j\|_2 + \|\vec{p}_j - \hat{\mathbf{H}} \cdot \vec{p}_i\|_2)$$

using manually selected control points $\vec{p}_i \leftrightarrow \vec{p}_j$.

❖ Top N selection leads to single point clusters with non-uniform distributions.

❖ ANMS and k-d tree method provide spatially well uniformed feature distributions.

➔ Mean registration errors of k-d tree partitioning and ANMS are smaller than for top N selection.

❖ ANMS and k-d tree provide low errors even for a small number of feature points.

❖ Number of inliers of ANMS higher than k-d tree partitioning. ➔ Lower registration error.

❖ ANMS $O((N-1)!)$ complexity higher than k-d tree with $O(\log N)$.

➔ Mean registration errors of image pairs can highly reduced, by ANMS and k-d tree feature distribution algorithms.

➔ High impact for real-time image mosaicking algorithms (e.g. medical computer assistance systems [1],[2]) using fixed and limited number of feature points.

References

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