Retina Project Overview

• Registration
  – Preoperative images to intraoperative images
  – Overlay of landmarks on live microscopic feed

• Requirements
  – Image Matching/Tracking
Paper Selection and Relevance

• SURF – algorithm for feature detection and descriptor generation

Background

• Computer Vision
  – Object recognition
  – Video tracking
• Finding point correspondence between 2 images
  – Feature detection, feature descriptor, feature matching
  – SIFT (Scale Invariant Feature Transform)
    • Slow for live video implementation
    • “Predecessor” / Influence
    • Hessian (location), Laplacian (scale) – approx via Difference of Gaussians
Problems

- Feature Detector
  - Repeatability
  - Robust
  - Distinct
  - Scale, rotation invariant

- Feature Descriptor
  - Robust to noise,
    detection displacement,
    geometric/photometric
deformations
  - Fewer dimensions = faster, but less distinct

SURF Theory: Feature Detector

- Feature Detector
  - Corners, blobs, T-junction
  - Integral Images
  - Hessian-matrix (choose where determinant is maximum)
  - Approximation
    - “Fast Hessian detector”
    - Small loss in repeatability

Given a point \( \mathbf{x} = (x, y) \) in an image \( I \), the Hessian matrix \( \mathcal{H}(\mathbf{x}, \sigma) \) in \( \mathbf{x} \) at scale \( \sigma \) is defined as follows

\[
\mathcal{H}(\mathbf{x}, \sigma) = \begin{bmatrix}
L_{xx}(\mathbf{x}, \sigma) & L_{xy}(\mathbf{x}, \sigma) \\
L_{xy}(\mathbf{x}, \sigma) & L_{yy}(\mathbf{x}, \sigma)
\end{bmatrix},
\]

(2)

where \( L_{xx}(\mathbf{x}, \sigma) \) is the convolution of the Gaussian second order derivative \( \frac{\partial^2}{\partial x^2} g(\sigma) \) with the image \( I \) in point \( \mathbf{x} \), and similarly for \( L_{xy}(\mathbf{x}, \sigma) \) and \( L_{yy}(\mathbf{x}, \sigma) \).

Fig. 2. Left to right: the (discretised and cropped) Gaussian second order partial derivative in \( y \) \( (L_{yy}) \) and \( xy \) direction \( (L_{xy}) \), respectively; our approximation for the second order Gaussian partial derivative in \( y \) \( (D_{yy}) \) and \( xy \) direction \( (D_{xy}) \). The grey regions are equal to zero.

Images and formulas taken from SURF paper.
**SURF Theory: Feature Detector**

- **Feature Detector**
  - Scale Invariant

  ![Scale Invariant Image](image)

  Fig. 4. Instead of iteratively reducing the image size (left), the use of integral images allows the up-scaling of the filter at constant cost (right).

**SURF Theory: Feature Descriptor**

- **Feature Descriptor**
  - Describing smaller-scale features within interest neighborhood
  - Closely mimics SIFT
  - Rotation invariant
  - Haar Wavelet Responses

  ![Rotation Invariant Image](image)

  Fig. 10. Orientation assignment: A sliding orientation window of size \( \ell \) detects the dominant orientation of the Gaussian-weighted Haar wavelet responses at every sample point within a circular neighbourhood around the interest point.
SURF Theory: Feature Descriptor

- Feature Descriptor
  - Describing smaller-scale features within interest neighborhood
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SURF Theory: Feature Matching

- Feature Matching
  - Sign of Laplacian (trace of Hessian)

Images and formulas taken from SURF paper
Experiment

- Comparison (speed, repeatability, reliability)
- Camera calibration for 3D reconstruction
- Object recognition experiment

Key Result – Feature Detection, Speed

<table>
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<tr>
<th>detector</th>
<th>threshold</th>
<th>nb of points</th>
<th>comp. time (ms)</th>
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<td>60000</td>
<td>1813</td>
<td>160</td>
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<td>DoG</td>
<td>default</td>
<td>1520</td>
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Table 1
Thresholds, number of detected points and calculation time for the detectors in our comparison. (First image of Graffiti scene, 800 × 640)
Key Result – Feature Detection, Repeatability

Images and formulas taken from SURF paper.

Key Result – Feature Descriptor

Recall precision for nearest-neighbor ratio matching.
Critique

Good
• Described previous related work/algorithm
• Extended SIRF/other related detector-descriptors
• Justification of theory
• Balanced Speed vs. Performance
• Relevance to other areas of research

Bad
• Faster, faster, faster → In-Depth Analysis of Performance?
• What ways is SURF better/worse than SIFT?
  – Need larger sample testing

Next Steps
• GPU Parallelization - Done
• Feature Descriptor : 64 vs. 128 elements
• Testing on image distortions
• Implications for image matching by comparing descriptors
• No color info used
Assessment / Relevance to Project

• Speed vs. Accuracy
  — Live tracking?
• Robustness for current data
  — Scale invariant
• Customizable – Hessian threshold, description size
• Feature matching?

Conclusion

• Balance between Speed vs. accuracy
  — Approximation, reduction in operations
• Valid replacement for SIFT
Questions?