Multi-resolution image recognition

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Outline

- Scale distribution
- Presentation of two different approaches and experiments
- Analysis of previous results

Motivation

- Typical image retrieval applications: similar resolution in database images and queries
- Performance drops when the resolutions are very different (high-res database image vs. low-res query)



• OK for some applications (product recognition), not ideal for others (large painting recognition)

Scale distribution – derivation

- Goal: Find the average distribution of scales for an "ideal" feature detector
- Hypotheses: continuous representation of the scales + a few assumptions on the feature detectors

Scale distribution – derivation

$$\begin{split} \rho(s) &\propto 1/s^3 \\ F(s) &= \left\{ \begin{array}{ll} 0 & \text{if } s \leq s_0 \\ 1 - s_0^2/s^2 & \text{if } s \geq s_0 \end{array} \right. \end{split}$$

• $F(2s_0) = 0.75 - Qualitative justification$



 $\{s_0 \le s \le 2s_0\}$ contains N-N/4 = 3N/4 features

Dataset used for the experiments

- Images extracted from a public art repository (Web Gallery of Art): more than 30,000 images
- We keep cropped regions of fixed size (17,146 images at resolution 1024x768)
- We generate queries of half the size of the database images (512x384) by rotating/scaling/translating



(zoom factor defined before downsampling)

Scale distribution – experiment



Scale distribution – results



Effect of discretized scale detector

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Scale distribution – results



 Power law: a bit of a stretch, but gives a rough idea of the behavior

Baseline (single REVV)

• Aggregate 250 SURF features with coarsest scale



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Tile based approach

• Each DB image is represented by 5 tiles



Scale based aggregation – Idea

- Main conclusion from previous analysis: most features have a scale in the interval [s₀, 2s₀]
 - 75% in theory
 - ~70% in practice (depends of size of query)
- Aggregate features according to scale domains and position



Scale based aggregation – Idea



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Scale based aggregation – Idea



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Scale based aggregation – Experiment

 Database side: case of limited scale variation, we only consider 2 levels



• Query side: we only have 2 bins ($s > 2s_0$ and $s < 2s_0$)

Scale based aggregation – Experiment



Scale based aggregation

- How do we merge the two lists?
 - 1. By cheating: we take the "best" rank in each list
 - 2. By using the correlation scores to re-rank the results
 - 3. By using a linear combination of the best correlation score for each image



Multi-scale experiments

• Zoom = 2x (query represents ~25% of original image)



Multi-scale experiments

• Zoom = 1.5x (query represents ~44% of original image)



Multi-scale experiments

• Zoom = 1x (query represents ~100% of original image)



Analysis of results

- Current problem of our approach: hard-binned scale (assumes good reproducibility of scale extraction)
- Justification of the good results obtained in the tiling approach: REVV and surface overlap

Scale reproducibility – experiment



Scale reproducibility – results



Scale reproducibility – results



REVV and surface overlap – experiment



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REVV and surface overlap – results

Precision at rank 10 for each type of tile



Conclusion of multi-resolution exploration

- Considerable unsolved issues
 - Scale reproducibility (try other values of thresholds)
 - Increased cost of running 2 queries, but no real gain in nonoptimal conditions
- The simpler (tile-based) approach is "too good"
 - Shows the robustness of REVV
- Hybrid approach?

Conclusion of multi-resolution exploration

Hybrid approach





Conclusion of multi-resolution exploration

Hybrid approach

