Video Google: Text Retrieval Approach to Object Matching in Videos

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Motivation

- Retrieve key frames and shots of video containing particular object with ease, speed and accuracy with which Google retrieves web pages containing particular words
- Investigate whether text retrieval approach is applicable to object recognition
- Visual analogy of word: vector quantizing descriptor vectors

Benefits

- Matches are pre-computed so at run time frames and shots containing particular object can be retrieved with no delay
- Any object (or conjunction of objects) occurring in a video can be retrieved even though there was no explicit interest in the object when the descriptors were built

Text Retrieval Approach

- Documents are parsed into words
- Words represented by stems
- Stop list to reject common words
- Remaining words assigned unique identifier
- Document represented by vector of weighted frequency of words
- Vectors organized in inverted files
- Retrieval returns documents with closest (angle) vector to query

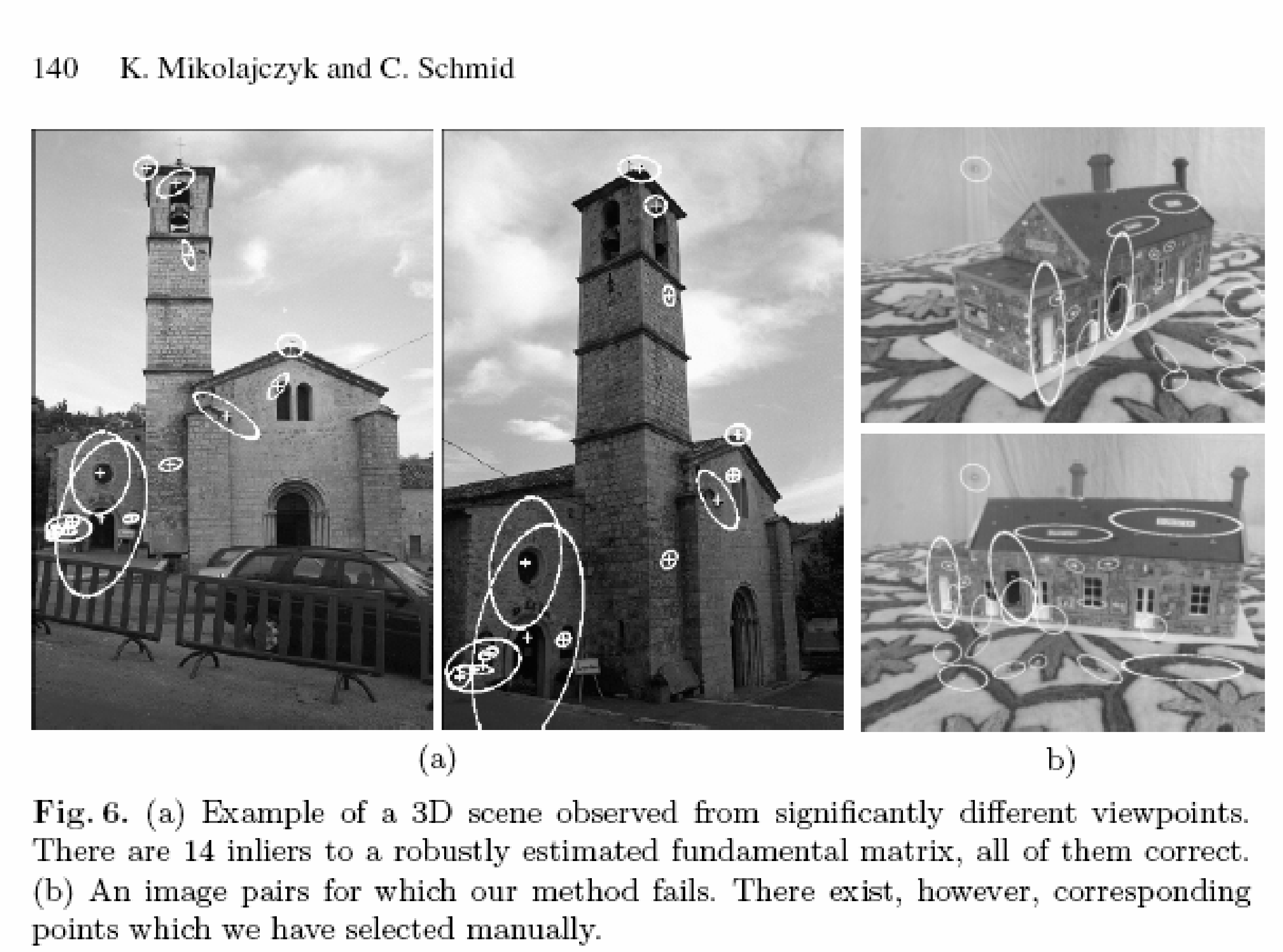
Viewpoint invariant description

- Two types of viewpoint covariant regions computed for each frame
  - Shape Adapted (SA) Mikolajczyk & Schmid
  - Maximally Stable (MS) Matas *et al.*
- Detect different image areas
- Provide complimentary representations of frame
- Computed at twice originally detected region size to be more discriminating

Shape Adapted Regions: the Harris-Affine Operator

- Elliptical shape adaptation about interest point
- Iteratively determine ellipse center, scale and shape
- Scale determined by local extremum (across scale) of Laplacian
- Shape determined by maximizing intensity gradient isotropy over elliptical region
- Centered on corner-like features

Examples of Harris-Affine Operator



140 K. Mikolajczyk and C. Schmid

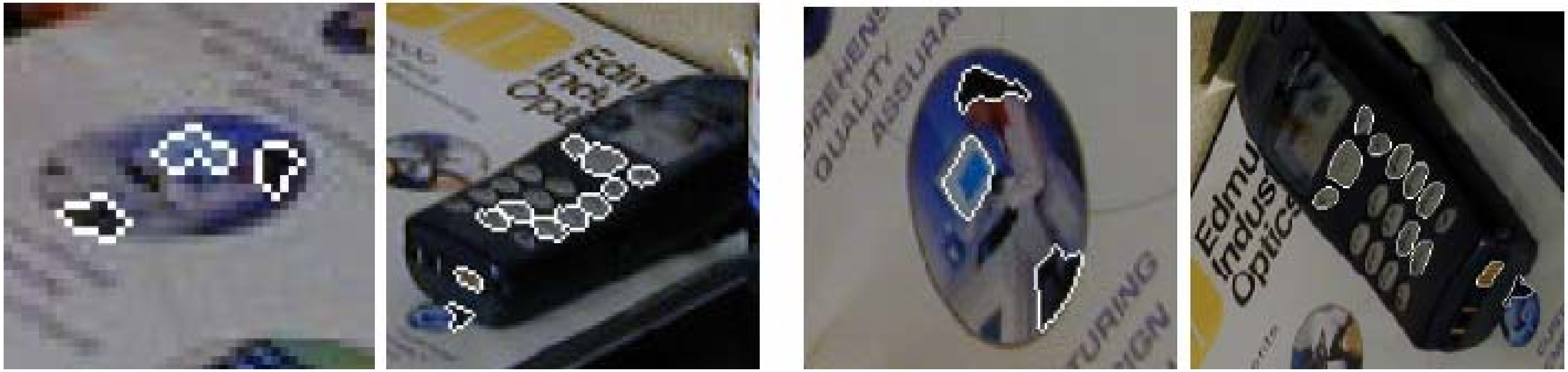
(a) b)

Fig. 6. (a) Example of a 3D scene observed from significantly different viewpoints. There are 14 inliers to a robustly estimated fundamental matrix, all of them correct. (b) An image pairs for which our method fails. There exist, however, corresponding points which we have selected manually.

Maximally Stable Regions

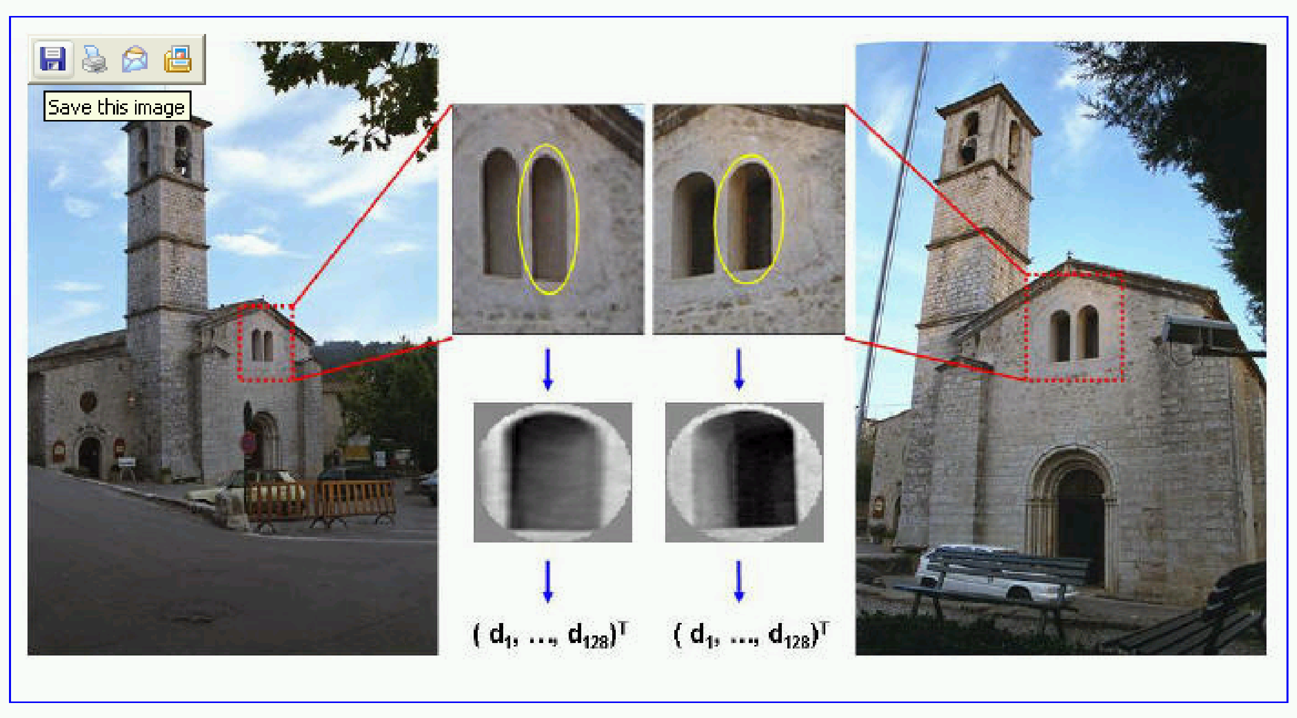
- Use intensity watershed image segmentation
- Select areas that are approximately stationary as intensity threshold is varied
- Correspond to blobs of high contrast with respect to surroundings

Examples of Maximally Stable Regions



Feature Descriptor

- Each elliptical affine invariant region represented by 128 dimensional vector using SIFT descriptor

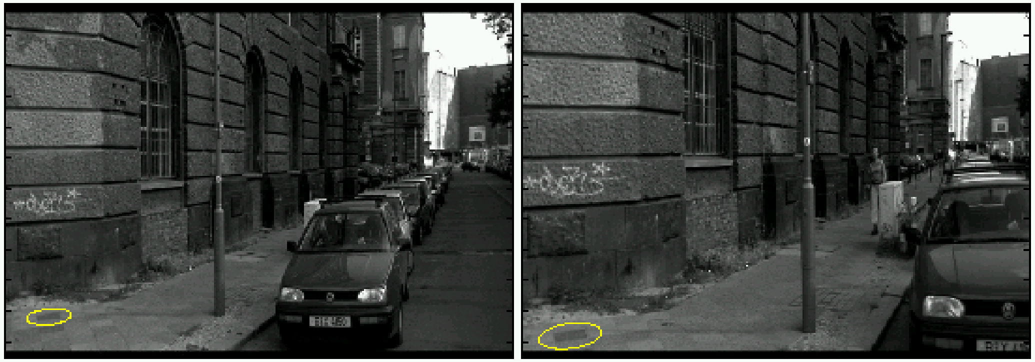


Noise Removal

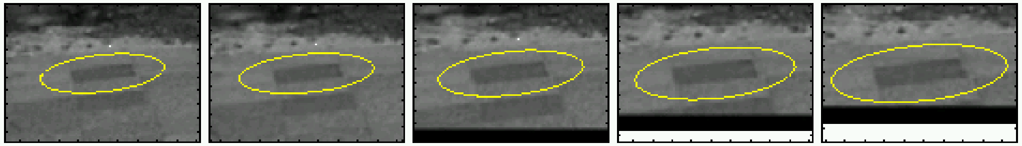
- Information aggregated over sequence of frames
- Regions detected in each frame tracked using simple constant velocity dynamical model and correlation
- Region not surviving more than 3 frames are rejected
- Estimate descriptor for region computed by averaging descriptors throughout track

Noise Removal

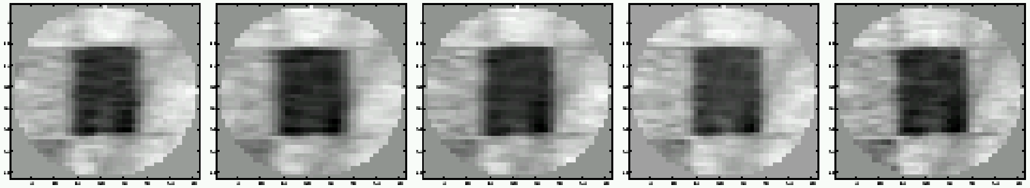
- **Tracking region over 70 frames**



First (left) and last (right) frame of the track.



Close-up of the 1st, 20th, 40th, 55th, 70th frame.



Visual Vocabulary

- Goal: vector quantize descriptors into clusters (visual words)

- When a new frame is observed, the descriptor of the new frame is assigned to the nearest cluster, generating matches for all frames

Visual Vocabulary

- Implementation: K-Means clustering
- Regions tracked through contiguous frames and average description computed
- 10% of tracks with highest variance eliminated, leaving about 1000 regions per frame
- Subset of 48 shots (~10%) selected for clustering
- Distance function: Mahalanobis
- 6000 SA clusters and 10000 MS clusters

Visual Vocabulary

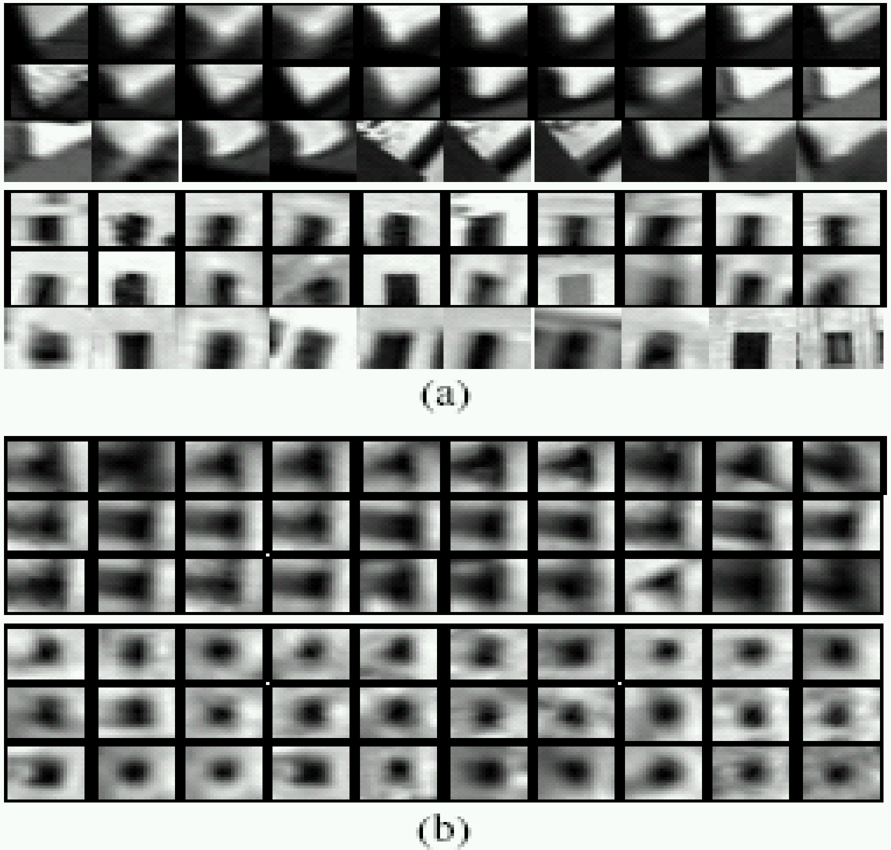
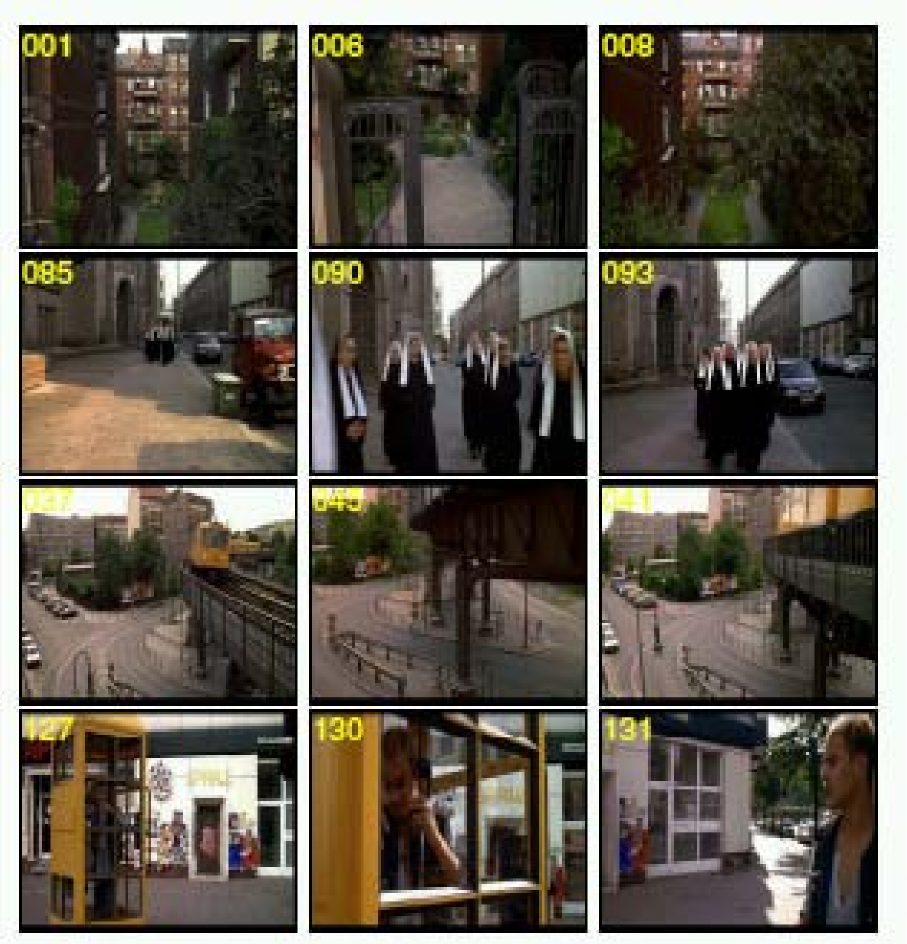


Figure 2: Samples from the clusters corresponding to a single visual word. (a) Two examples of clusters of Shape Adapted regions. (b) Two examples of clusters of Maximally Stable regions.

Experiments - Setup

- Goal: match scene locations within closed world of shots
- Data:164 frames from 48 shots taken at 19 different 3D locations; 4-9 frames from each location



Experiments - Retrieval

- Entire frame is query
- Each of 164 frames as query region in turn
- Correct retrieval: other frames which show same location
- Retrieval performance: average normalized rank of relevant images

$$\widetilde{Rank} = \frac{1}{NN_{rel}}\left(\sum_{i=1}^{N_{rel}} R_i - \frac{N_{rel}(N_{rel}+1)}{2}\right)$$

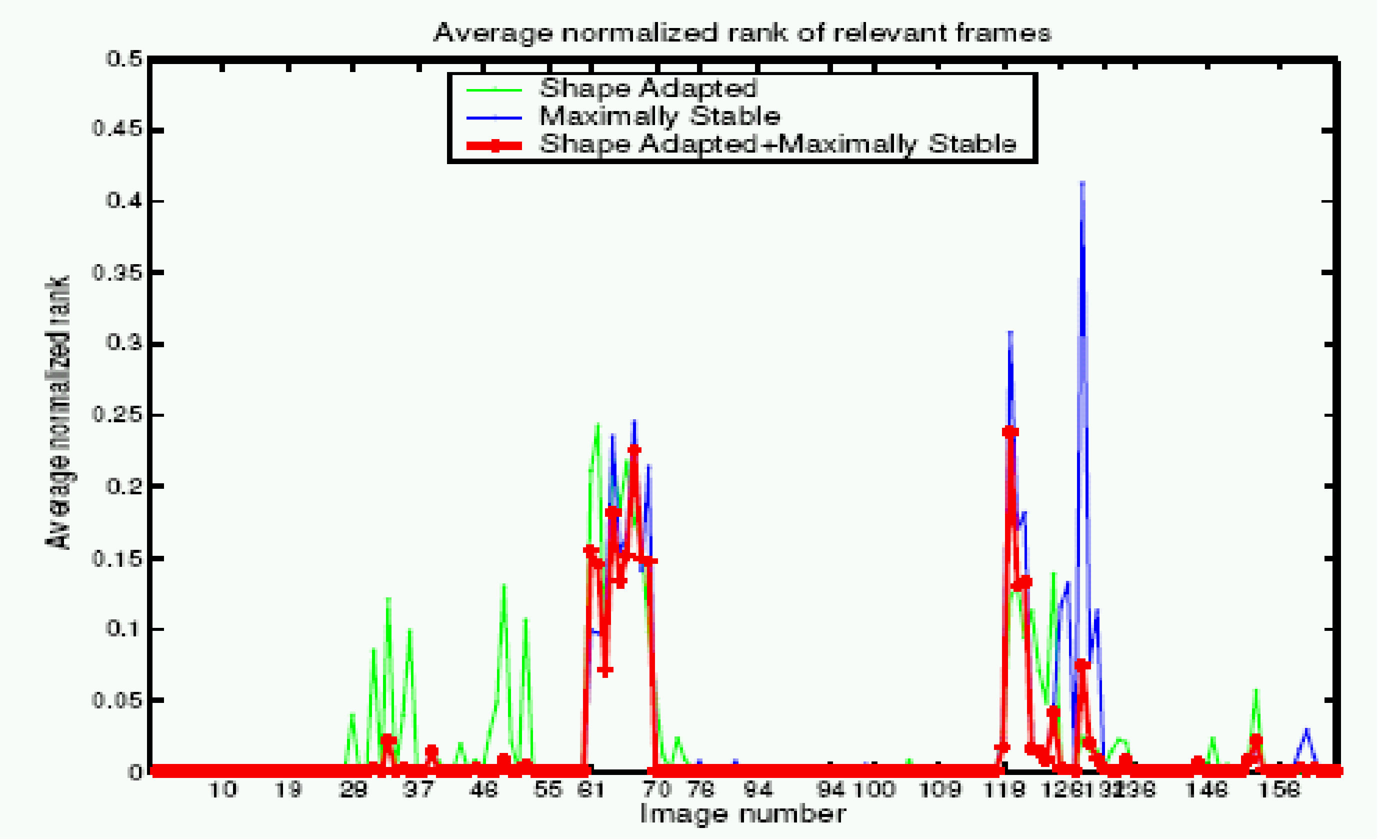
N_{rel} = # of relevant images for query image

N = size of image set

R_i = rank of ith relevant image

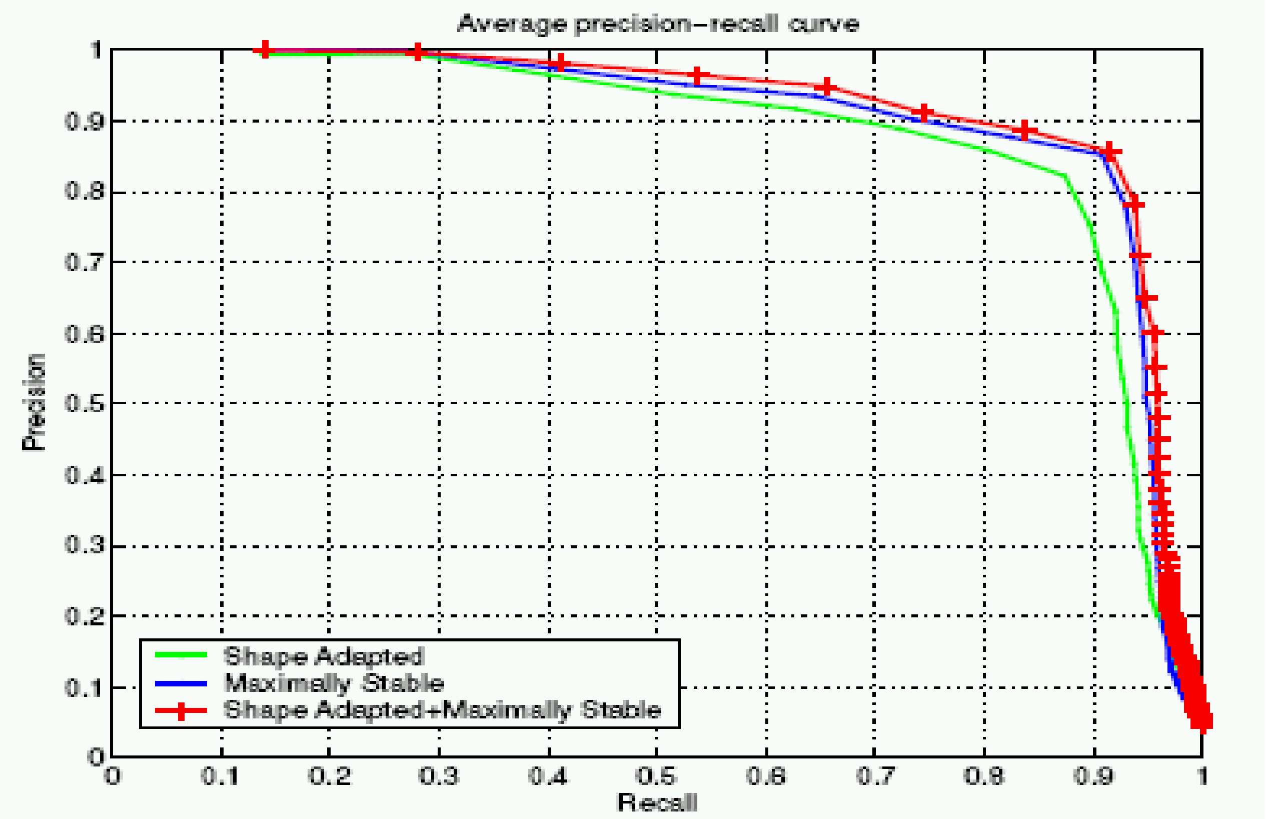
Rank lies between 0 and 1.
Intuitively, it will be 0 if all relevant images are returned ahead of any others.
It will be .5 for random retrievals.

Experiment - Results



Zero is good!

Experiments - Results



Precision = # relevant images/total # of frames retrieved

Recall = # correctly retrieved frames/ # relevant frames

Stop List

- Top 5% and bottom 10% of frequent words are stopped

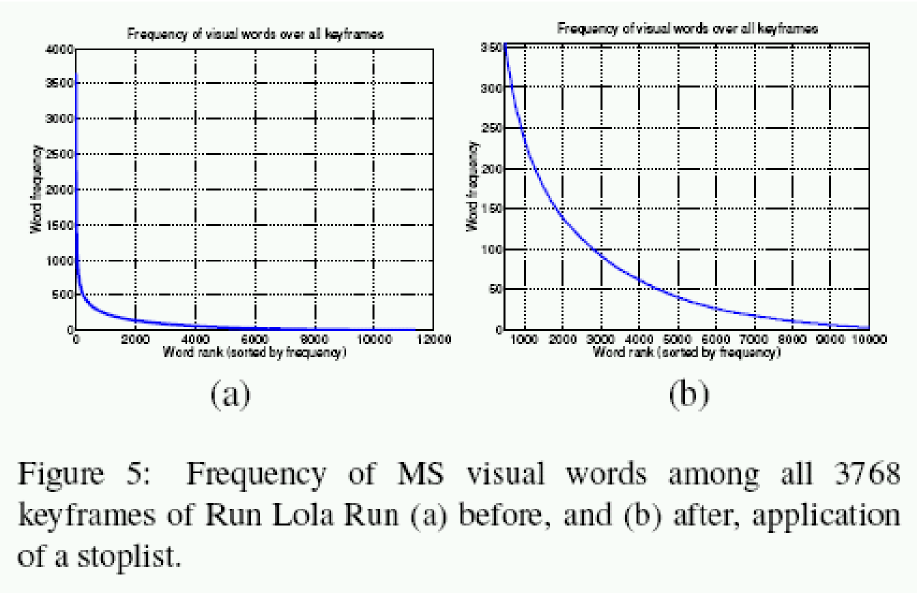


Figure 5: Frequency of MS visual words among all 3768 keyframes of Run Lola Run (a) before, and (b) after, application of a stoplist.

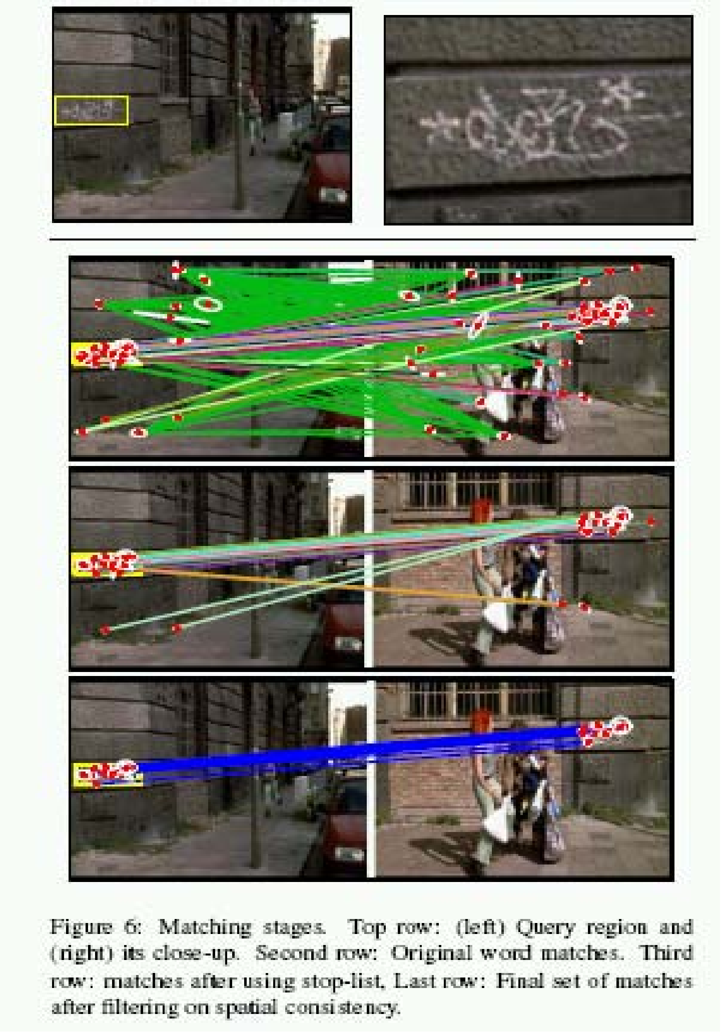


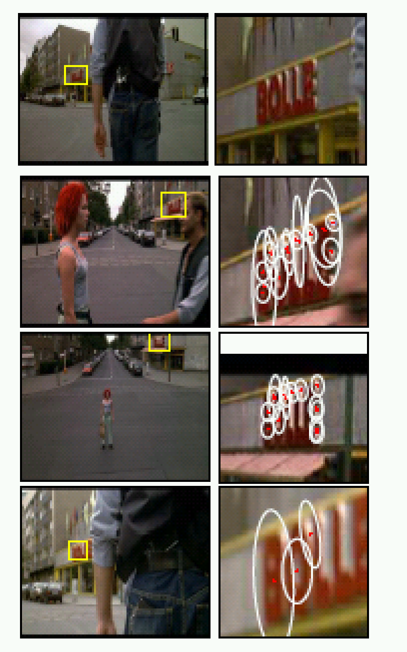
Figure 6: Matching stages. Top row: (left) Query region and (right) its close-up. Second row: Original word matches. Third row: matches after using stop-list, Last row: Final set of matches after filtering on spatial consistency.

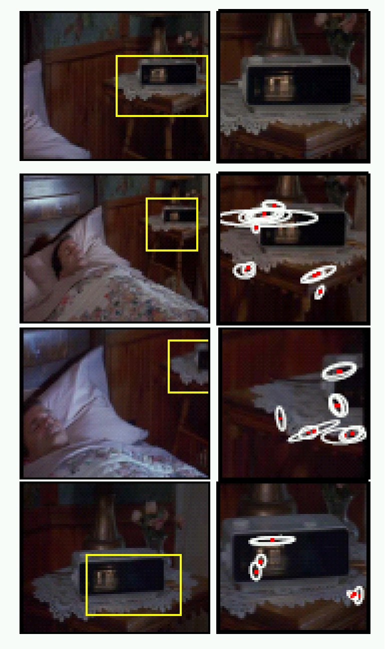
Spatial Consistency

- Matched region in retrieved frames have similar spatial arrangement to outlined region in query

- Retrieve frames using weighted frequency vector and re-rank based on spatial consistency

More Results





Demo

- http://www.robots.ox.ac.uk/~vgg/research/vgoogle/how/method/method_a.html
- http://www.robots.ox.ac.uk/~vgg/research/vgoogle/index.html