Deformable Wide Baseline Matching using Markov Random Fields

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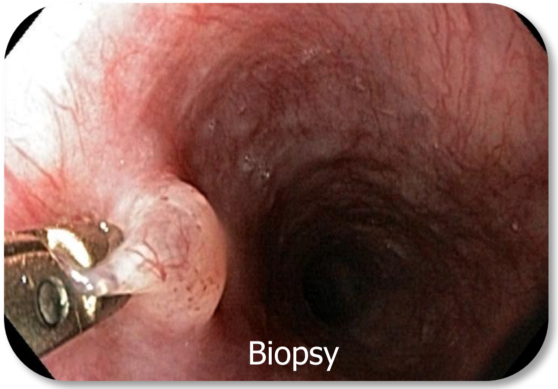
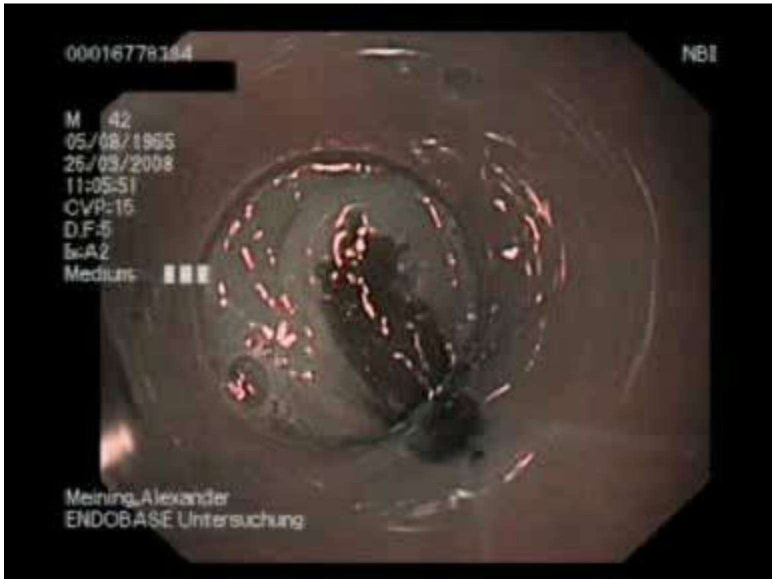
3 Department of Gastroenterology, Technische Universität München

Motivation

- *Oesophageal cancer* is the most rapidly increasing cancer is USA and in western world
- Survival rate is about *10 %*
- *Barrett's Oesophagus* is the only recognized precursor
- ***Periodic*** endoscopic examination and biopsy acquisition is highly recommended
- Recent developments enabled non-invasive *optical biopsy* for the clinical routine



Motivation – Retargeting Optical Biopsies



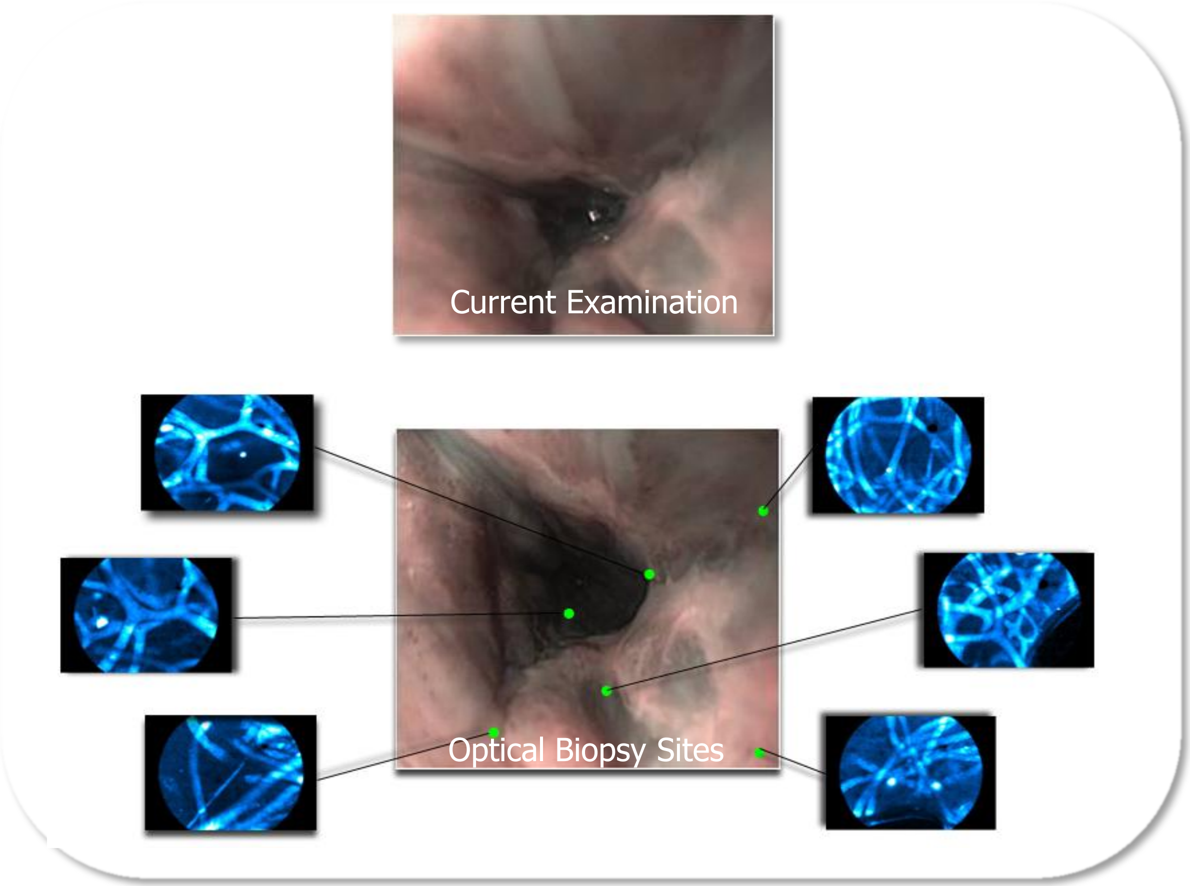
Optical Biopsy using FCM: Real-time, *in-vivo* and *in-situ* visualization of cellular structures

+ Real-time feedback
+ Non-invasive
± No scar on the tissue

Motivation - Retargeting Optical Biopsies

Goal:

Automatic Region Matching for Targeted Optical Biopsy



Problem Statement

Region matching in endoscopic images entails several challenges:

- Wide base-line matching
- Tissue deformation
- Similar surface textures
- Lack of distinctive features

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Wide base-line matching:

1. Detection of distinctive local regions (features) in the images

[1] Lowe, D.: Distinctive Image Features from Scale-Invariant Keypoints, Int. Journal of Computer Vision, (2004).

[2] Mikolajczyk, K. and Tuytelaars, T. and Schmid, C. and Zisserman, A. and Matas, J. and Schaffalitzky, F. and Kadir, T. and Gool, L.V.: A Comparison of Affine Region Detectors, Int. Journal of Computer Vision, (2005).

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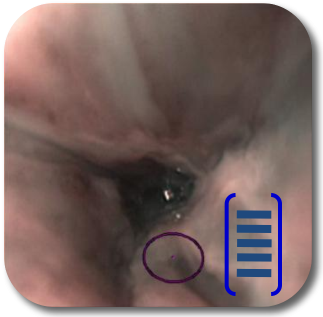

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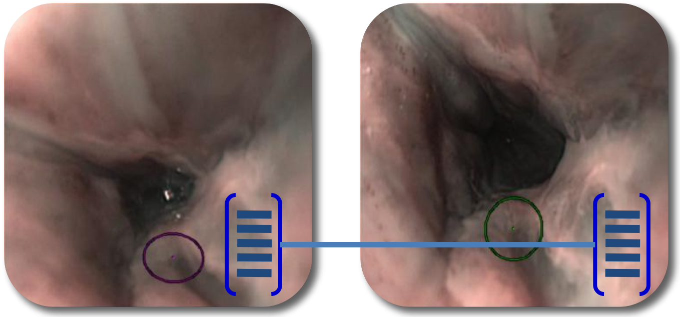

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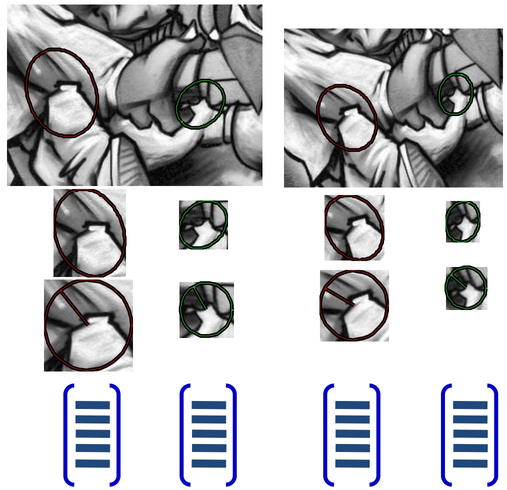
3. Matching the descriptors in both images

State-of-the Art

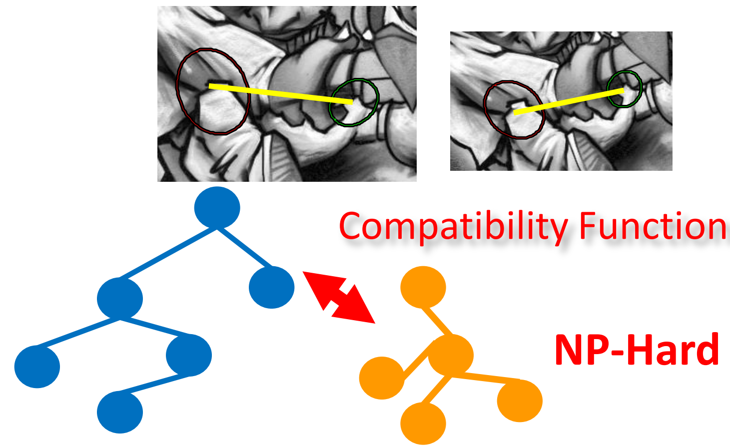
Bag-of-features

Discriminative region descriptors



Global Methods

Contextual relations between regions



[6] Lowe, D.: Distinctive Image Features from Scale-Invariant Keypoints, Int. Journal of Computer Vision, (2004).

[7] Sivic, J. and Zisserman, A.: Video Google: a text retrieval approach to object matching in videos, ICCV, (2003)

[8] Schaffalitzky, F. and Zisserman, A. Automated location matching in movies, Computer Vision and Image Understanding, Elsevier, (2003)

- Ambiguities due to non-distinctive features
- No geometric model due to large tissue deformation

[9] Zass, R. and Shashua, A.: Probabilistic graph and hypergraph matching, CVPR, (2008)

[10] Torresani, L., Kolmogorov, V., and Rother, C.: Feature Correspondence via Graph Matching: Models and Global Optimization, ECCV, (2008)

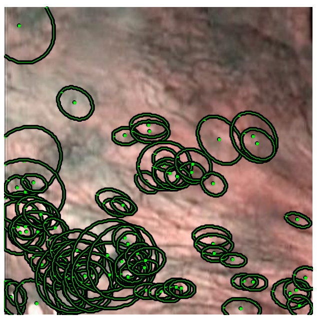
[11] Leordeanu, M. and Hebert, M.: A spectral technique for correspondence problems using pairwise constraints, ICCV, (2005)

[12] Caetano, T.; Cheng, L.; Le, Q. and Smola, A.: Learning graph matching, ICCV, (2007)

- Local geometric constraints as point locations

Matching through Markov Random Fields

Given n variables (**nodes**) $\mathcal{G} = \{1,..,n\}$, where each node can take values from a **label set** $\mathcal{L}^{+} = \{l_0, l_1, .., l_M\}$, compute the optimum **labelling** $\mathbf{l}^{*}$ (assignment of values to all variables).



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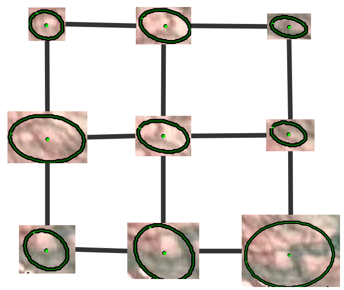

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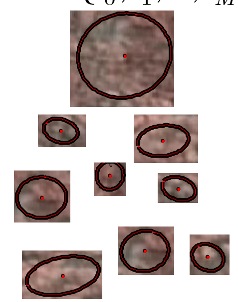

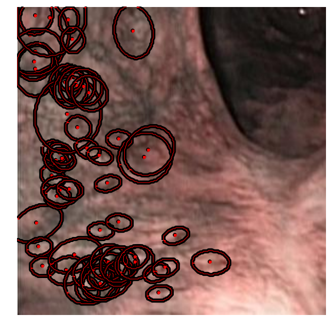

[13] Atasoy, S., Glocker, B., Giannarou, S., Mateus, D., Meining, A., Yang, G.Z., Navab, N.: Probabilistic Region Matching in Narrow-Band Endoscopy for Targeted Optical Biopsy, Medical Image Computing and Computer Assisted Intervention (MICCAI), (2009).

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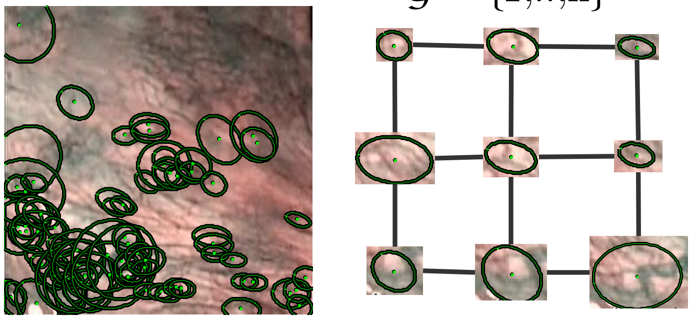
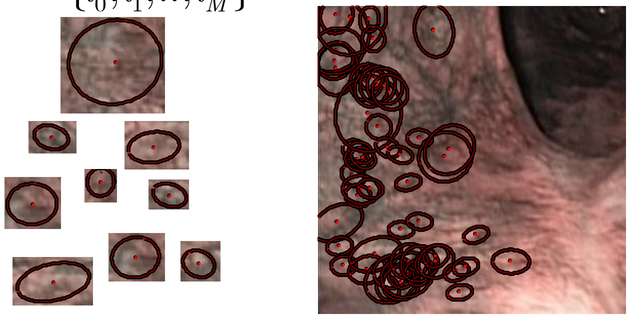
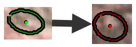


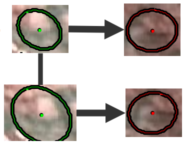


$$\mathbf{l}^{*} = \arg\min_{\mathbf{l}} \left[E_{\mathrm{MRF}}(\mathbf{l}) \right] = \arg\min_{\mathbf{l}} \left[\sum_{\mathrm{p} \in \mathcal{G}} V_{\mathrm{p}}(l_{\mathrm{p}}) + \sum_{\mathrm{p} \in \mathcal{G}} \sum_{\mathrm{q} \in \mathcal{N}(\mathrm{p})} V_{\mathrm{pq}}(l_{\mathrm{p}}, l_{\mathrm{q}}) \right]$$

Unary costs



Pairwise costs



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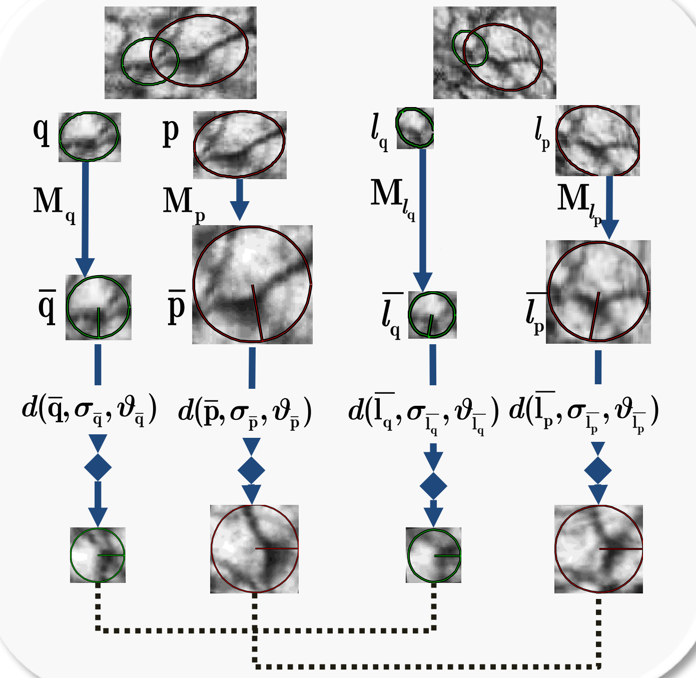
Unary Costs

- Photometric similarities between regions
- Viewpoint invariant region description
  1. Detecting affine covariant regions

     [14] Giannarou, S., Visentini-Scarzanella,M.,Yang, G.Z.: Affine-Invariant Anisotropic Detector For Soft Tissue Tracking in Minimally Invasive Surgery, ISBI, (2009).
  2. Normalizing for the affine transformation
  3. Computing the descriptor vector using the characteristic scale σ_{p} and the dominant gradient orientation ϑ_{p} of each patch p

     [15] Lowe, D.: Distinctive Image Features from Scale-Invariant Keypoints, Int. Journal of Computer Vision, (2004).



$$V_{\mathrm{p}}(l_{\mathrm{p}}) = \begin{cases} \dfrac{\arccos(d(\bar{\mathrm{p}},\sigma_{\bar{\mathrm{p}}},\vartheta_{\bar{\mathrm{p}}}) \cdot d(\bar{l}_{\mathrm{p}},\sigma_{\bar{l}_{\mathrm{p}}},\vartheta_{\bar{l}_{\mathrm{p}}}))}{\arccos(0)} & \text{if } l_{\mathrm{p}} \neq l_0 \\ \alpha \cdot (1 - \min(V_{\mathrm{p}}(\cdot))) & \text{otherwise} \end{cases}$$

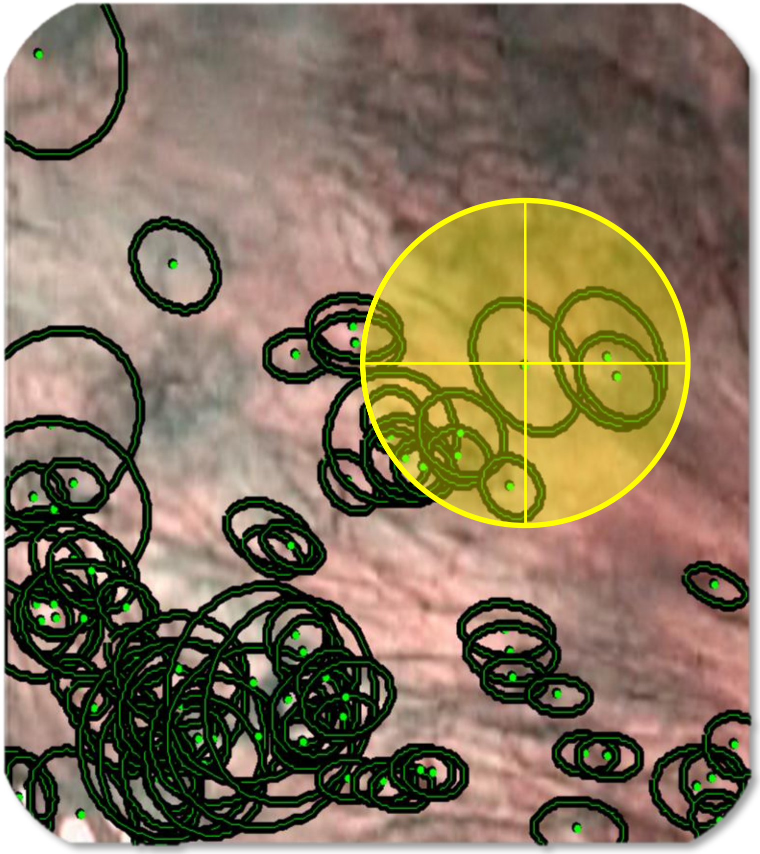
Photometric Similarities

Null-cost Function

Neighbourhood Systems

- Global neighbourhood system
  - Fully connected graph:
    $$\mathcal{N}(\mathrm{p}) = \{\mathrm{q}\}, \mathrm{q} \in \mathcal{G}$$
  - Uniqueness constraint:
    $$V_{\mathrm{pq}}(l_{\mathrm{p}}, l_{\mathrm{q}}) = \infty, \quad \text{if } l_{\mathrm{p}} = l_{\mathrm{q}} \neq l_0$$

- Local neighbourhood system
  - Defined for both, the nodes and the labels
  - Euclidean distance between region centres:
    $$\mathcal{N}_{\mathrm{local}}(\mathrm{p}) = \{\mathrm{q} \neq \mathrm{p} \mid \ \| \mathrm{p} - \mathrm{q} \| < t\}$$



Pair-wise Costs

- Uniqueness constraint: *"Each label can be assigned at most to one node"*
- Null-cost function: *"The cost of not matching a region"*
- Geometric constraints: *"Geometric consistency between matches"*

$$V_{\mathrm{pq}}(l_{\mathrm{p}}, l_{\mathrm{q}}) = \begin{cases} \infty & \text{if } (l_{\mathrm{p}} = l_{\mathrm{q}} \neq l_0) \\ \alpha & \text{if } (l_{\mathrm{p}} = l_0) \vee (l_{\mathrm{q}} = l_0) \\ \psi_{\mathrm{pq}}(l_{\mathrm{p}}, l_{\mathrm{q}}) & \text{if } (\mathrm{q} \in \mathcal{N}_{\mathrm{local}}(\mathrm{p})) \\ 0 & \text{otherwise} \end{cases}$$

Uniqueness Constraint

Null-cost Function

Geometric Constraints

Pair-wise Costs - Geometric Constraints

1. Neighbourhood preservation:

   "Close regions tend to be close in the second image"

2. Transformation constraint

   *"Close regions move with **similar** transformations between two images"*

$$\psi_{pq}(l_p, l_q) = \begin{cases} \infty & \text{if } (l_p \notin \mathcal{N}_{local}(l_q)) \\ \dfrac{\arccos(d(\bar{q}, \sigma_{\bar{q}}, \vartheta_{\bar{p}}) \cdot d(\bar{l}_q, \sigma_{\bar{l}_q}, \vartheta_{\bar{l}_p}))}{\arccos(0)} & \text{if } (l_p \in \mathcal{N}_{local}(l_q)) \end{cases}$$

Neighbourhood Preservation

Transformation Constraints

Pair-wise Costs - Geometric Constraints

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Neighbourhood Preservation (first case)

Transformation Constraints (second case)

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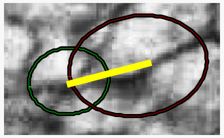
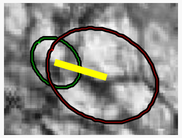


p q



l_p l_q

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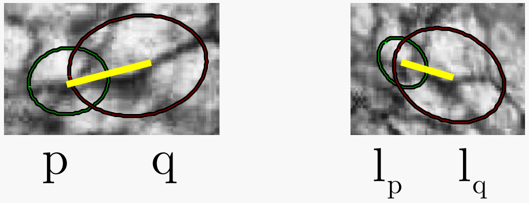

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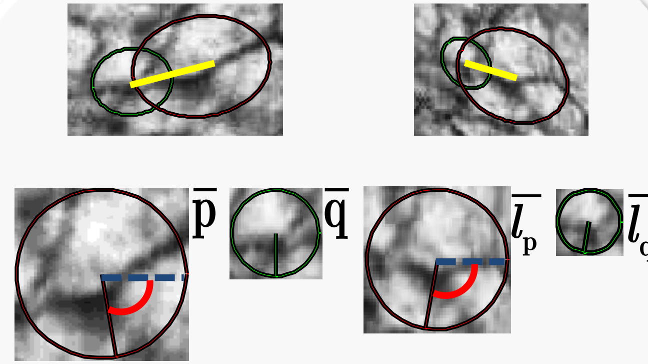

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Neighbourhood Preservation (first case)

Transformation Constraints (second case)

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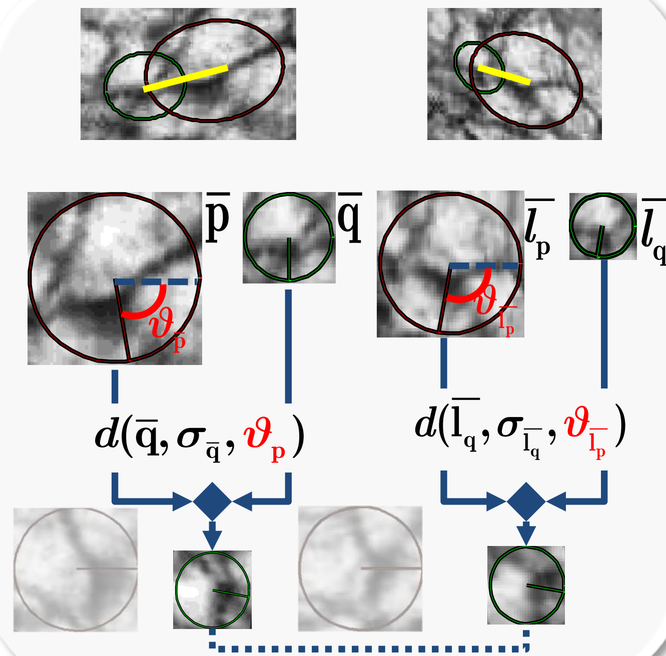

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Neighbourhood Preservation

Transformation Constraints

Pair-wise Costs - Geometric Constraints

1. Neighbourhood preservation:

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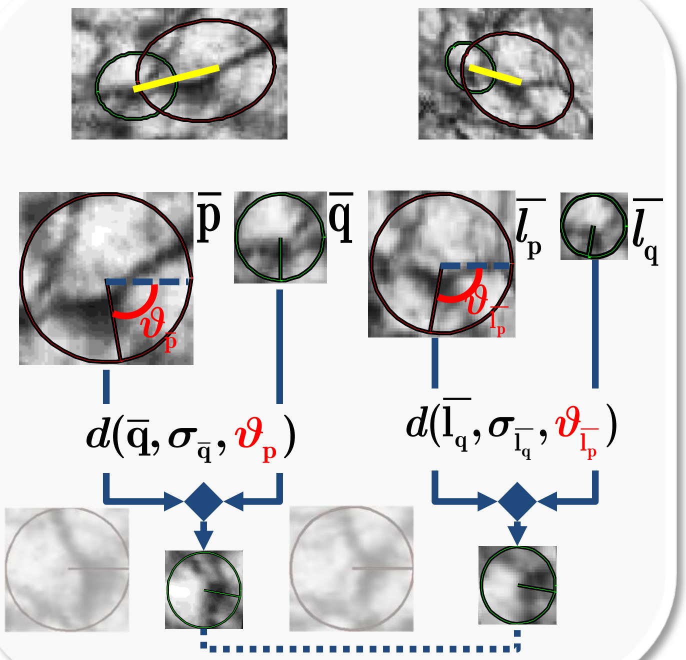
2. Transformation constraint

   *"Close regions move with **similar** transformations between two images"*

- \+ Robust to deviations in relative positioning of regions
- \+ Use of discriminative power of region descriptors for geometric constraints
- \+ Evaluation of appearance and geometric constraints in the same space



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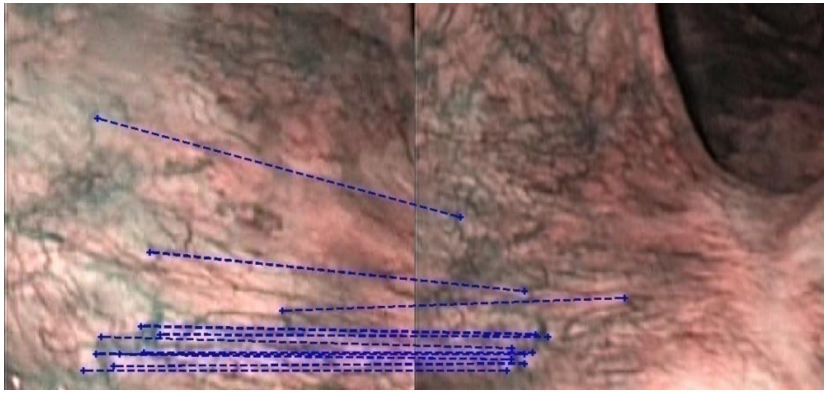
Neighbourhood Preservation

Transformation Constraints

Matching through Markov Random Fields

- Compute the optimum labelling by minimizing the MRF energy function using the Belief Propagation method

[14] Pearl, J.: Probabilistic Reasoning, San Francisco, CA: Morgan Kaufmann, (1988)



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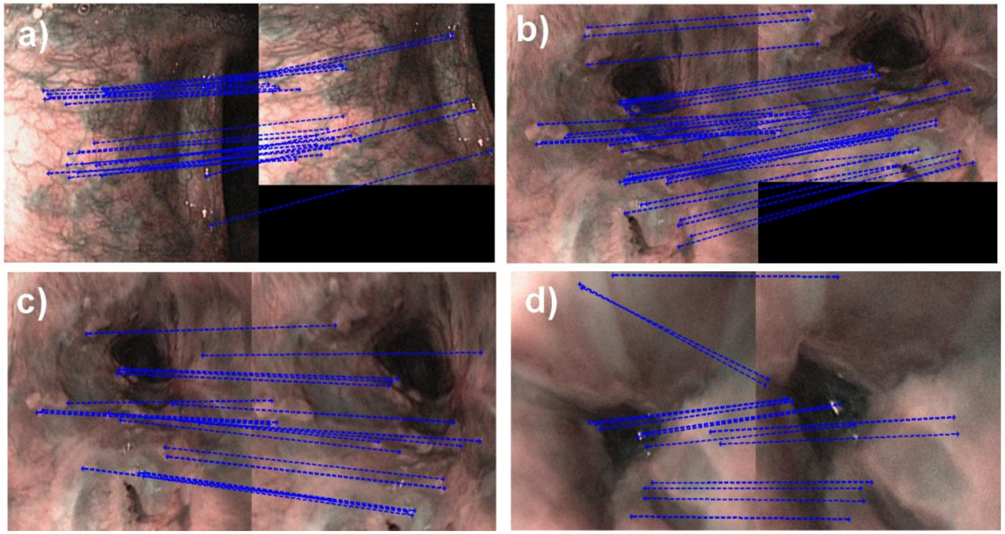
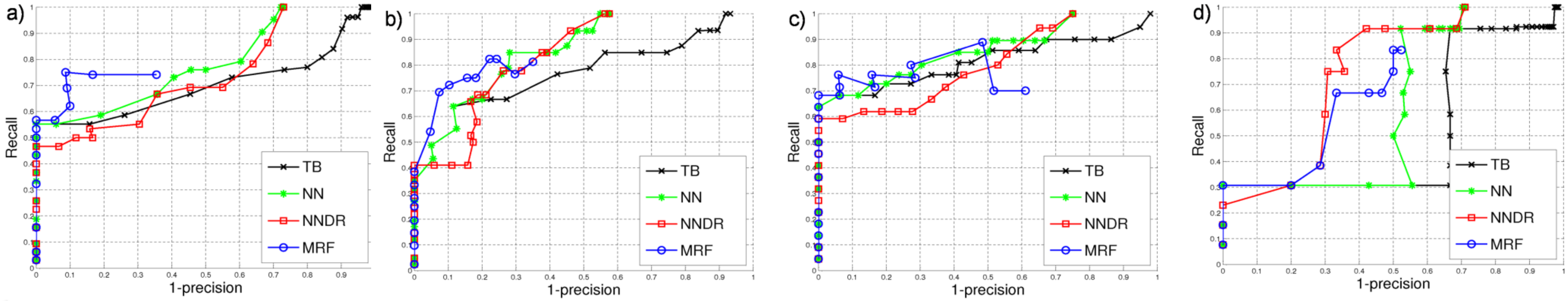
Unary costs **Pairwise costs**

Results – Simulation Data

- Comparison to
  - Nearest-neighbour matching (NN)
  - Threshold-based matching (TB)
  - Nearest-neighbour distance ratio matching (NNDR)

[15] Mikolajczyk, K. and Schmid, C.: A Performance Evaluation of Local Descriptors, PAMI, (2005)

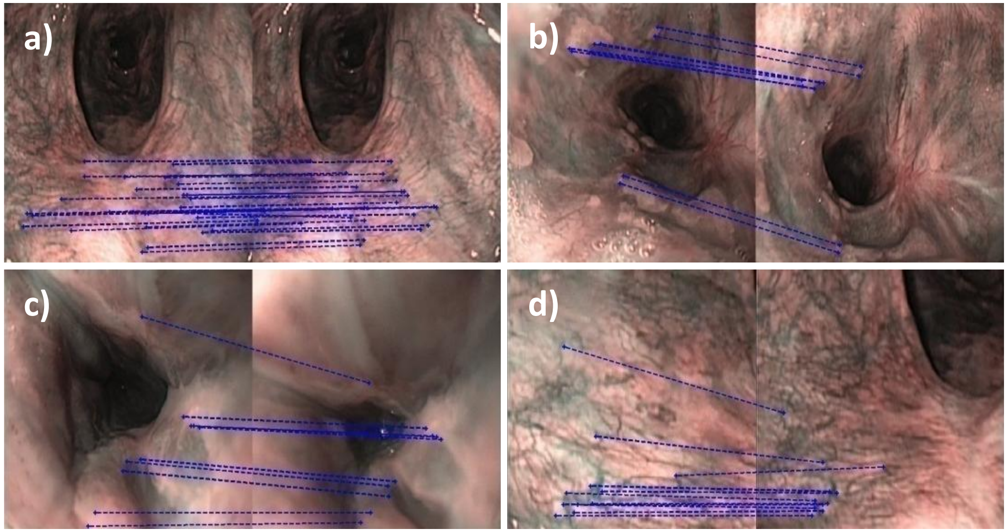


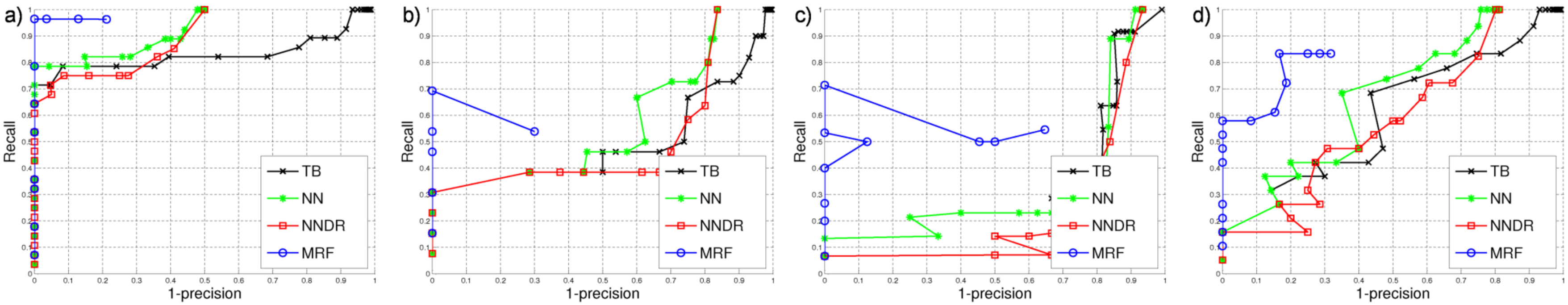


Results – In-Vivo Data

- Comparison to
  - Nearest-neighbour matching (NN)
  - Threshold-based matching (TB)
  - Nearest-neighbour distance ratio matching (NNDR)

[15] Mikolajczyk, K. and Schmid, C.: A Performance Evaluation of Local Descriptors, PAMI, (2005)





Conclusion & Future Work

- MRF model for deformable wide base-line matching
- A novel geometric constraint, which
  - is robust to changes in relative feature positioning
  - is evaluated on photometric image properties
  - uses the discriminative power of region descriptors by evaluating geometry
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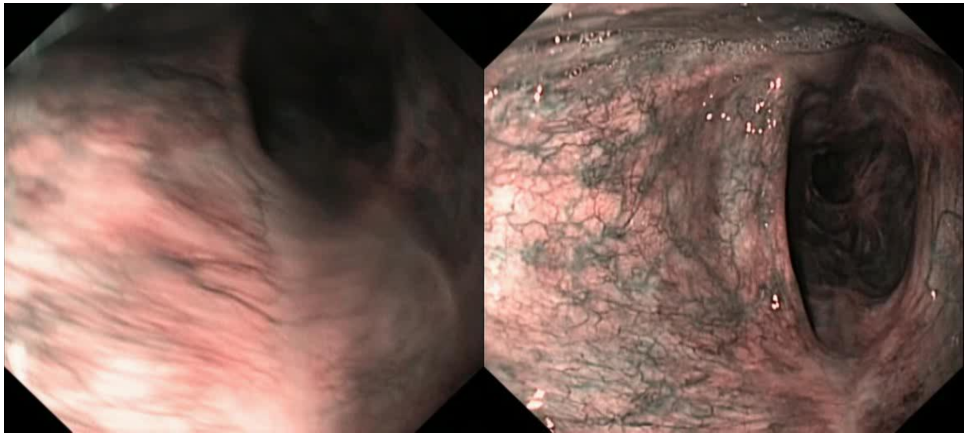
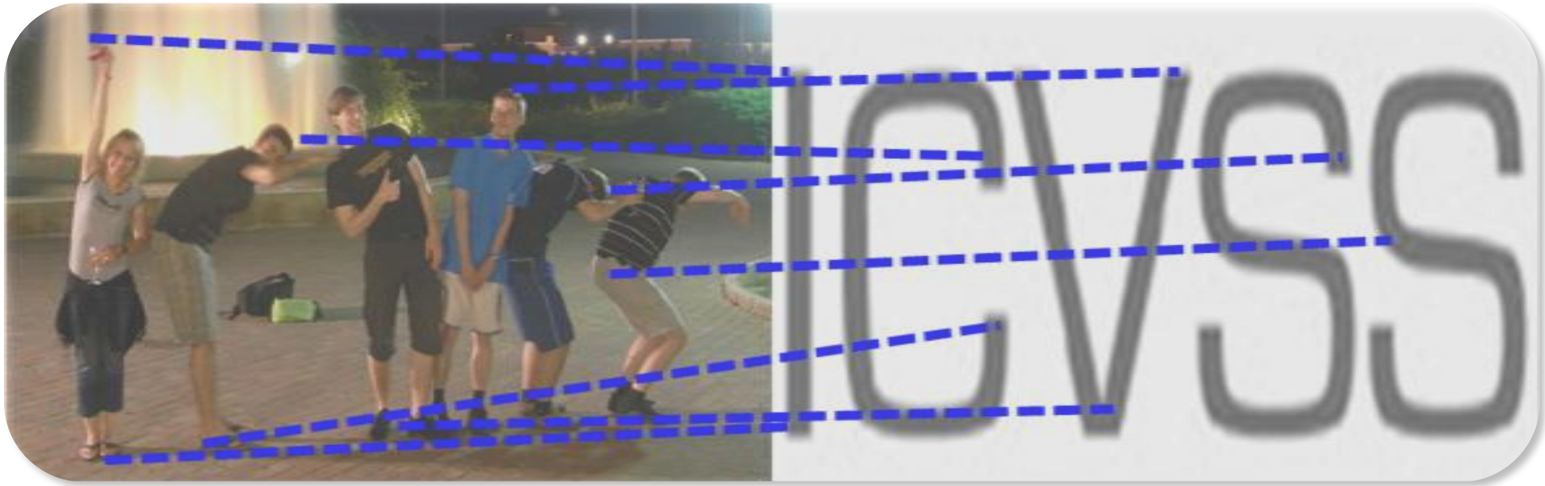
- Future Work:

  Framework using the temporal information of the video content





Thank you for your attention!