Radiograph Annotation using Local Relational Features

Lokesh Setia, Alexandra Teynor, Alaa Halawani and Hans Burkhardt

Institute for Computer Science
University of Freiburg

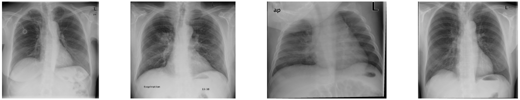
CLEF 2006

Introduction
Radiograph Annotation Problem

- Set of tags to be attached to each X-ray image
- e.g. “*x-ray, plain radiography, coronal, upper extremity (arm), hand, musculosceletal system*”
- Provided database used only 116 combinations
- Flat classification scheme was used!

Database Characteristics

- High number of classes (116)
- High intra-class variibility (position, small rotation, occlusion, cropping)
- Some classes with very low inter-class variibility (e.g. classes 108, 109, 110 and 111)



Algorithm

A local feature based approach:

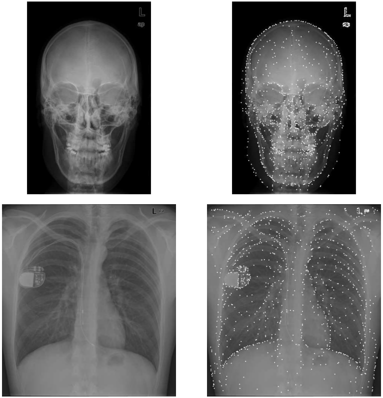
a. Calculate relational features around interest points for all training images
b. Cluster using *k-means*
c. Build a cluster cooccurrence matrix (CCM) from cluster indices
d. Train a multi-class SVM using CCMs as features

For a test image:

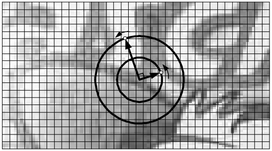
e. Repeat steps [a] and [c], using cluster indices from step [b]
f. Assign label using trained multi-class SVM output.

Interest Point Detector

The Loupias wavelet-based detector is used



Relational Features



- Based on gradient in various directions and scales
- *rel* function makes gradient robust to affine brightness changes

$$\mathrm{rel}(x) = \begin{cases} 1 & \text{if } x < -\epsilon \\ \frac{\epsilon - x}{2\epsilon} & \text{if } -\epsilon \leq x \leq \epsilon \\ 0 & \text{if } \epsilon < x \end{cases},$$

- 3 scales, and 12 directions/scale are used $\rightarrow$ 36 dimension feature vector

Building final feature vector

a) 1-D Cluster Membership Histogram

$$\mathbf{F}(c) = \#\{\mathbf{s} \mid (I(\mathbf{s}) = c)\}, \quad c = 1, \ldots, N_c$$

b) 3-D Cluster Cooccurrence Histogram (Rotation Invariant)

$$\begin{aligned}\mathbf{F}(c_1, c_2, d) = \#\{(\mathbf{s}_1, \mathbf{s}_2) \mid\ & (I(\mathbf{s}_1) = c_1) \wedge (I(\mathbf{s}_2) = c_2) \\ & \wedge (D_d < \|\mathbf{s}_1 - \mathbf{s}_2\|_2 < D_{d+1})\}\end{aligned}$$

c) 4-D Cluster Cooccurrence Histogram (Not Rotation Invariant)

$$\begin{aligned}\mathbf{F}(c_1, c_2, d, a) = \#\{(\mathbf{s}_1, \mathbf{s}_2) \mid\ & (I(\mathbf{s}_1) = c_1) \wedge (I(\mathbf{s}_2) = c_2) \\ & \wedge (D_d < \|\mathbf{s}_1 - \mathbf{s}_2\|_2 < D_{d+1}) \\ & \wedge (A_a < \measuredangle(\mathbf{s}_1, \mathbf{s}_2) < A_{a+1})\}\end{aligned}$$

Building final feature vector

a) 1-D Cluster Membership Histogram

$$\mathbf{F}(c) \quad = \quad \#\{\mathbf{s} \quad | \quad (I(\mathbf{s}) = c)\}, \qquad c = 1, \ldots, N_c$$

b) 3-D Cluster Cooccurrence Histogram (Rotation Invariant)

$$\begin{aligned}\mathbf{F}(c_1, c_2, d) \quad = \quad \#\{\,(\mathbf{s}_1, \mathbf{s}_2) \quad | \quad & (I(\mathbf{s}_1) = c_1) \wedge (I(\mathbf{s}_2) = c_2) \\ & \wedge (D_d < ||\mathbf{s}_1 - \mathbf{s}_2||_2 < D_{d+1})\,\}\end{aligned}$$

c) 4-D Cluster Cooccurrence Histogram (Not Rotation Invariant)

$$\begin{aligned}\mathbf{F}(c_1, c_2, d, a) \quad = \quad \#\{\,(\mathbf{s}_1, \mathbf{s}_2) \quad | \quad & (I(\mathbf{s}_1) = c_1) \wedge (I(\mathbf{s}_2) = c_2) \\ & \wedge (D_d < ||\mathbf{s}_1 - \mathbf{s}_2||_2 < D_{d+1}) \\ & \wedge (A_a < \measuredangle(\mathbf{s}_1, \mathbf{s}_2) < A_{a+1})\,\}\end{aligned}$$

Building final feature vector

a) 1-D Cluster Membership Histogram

$$\mathbf{F}(c) \;=\; \#\{\mathbf{s} \;\mid\; (l(\mathbf{s}) = c)\}, \quad c = 1, \ldots, N_c$$

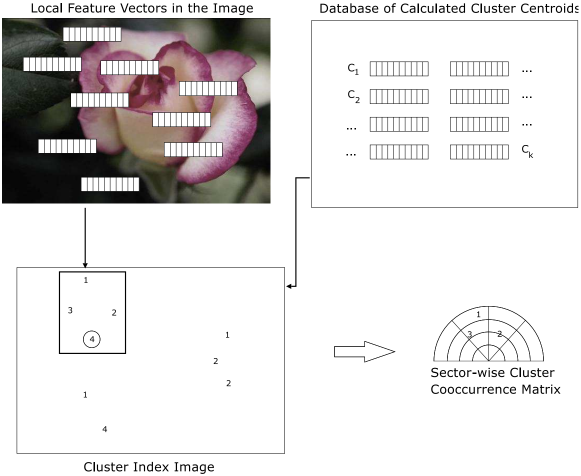
b) 3-D Cluster Cooccurrence Histogram (Rotation Invariant)

$$\mathbf{F}(c_1, c_2, d) \;=\; \#\{\, (\mathbf{s}_1, \mathbf{s}_2) \;\mid\; (l(\mathbf{s}_1) = c_1) \wedge (l(\mathbf{s}_2) = c_2) \wedge (D_d < ||\mathbf{s}_1 - \mathbf{s}_2||_2 < D_{d+1}) \,\}$$

c) 4-D Cluster Cooccurrence Histogram (Not Rotation Invariant)

$$\mathbf{F}(c_1, c_2, d, a) \;=\; \#\{\, (\mathbf{s}_1, \mathbf{s}_2) \;\mid\; (l(\mathbf{s}_1) = c_1) \wedge (l(\mathbf{s}_2) = c_2) \wedge (D_d < ||\mathbf{s}_1 - \mathbf{s}_2||_2 < D_{d+1}) \wedge (A_a < \measuredangle(\mathbf{s}_1, \mathbf{s}_2) < A_{a+1}) \,\}$$

Generating Cluster Cooccurrence Matrix



Results

- Error Rate for 116-category classification task: 16.7 %
- Ranked 2^{nd} for the ImageCLEF 2006 medical annotation task, 0.5% higher than best
- Outperformed other algorithms for the ImageCLEF 2005 radiograph database

Results
Nearest Neighbour (1)

10251.png (64)
d=0.0

14195.png (64)
d=99.9

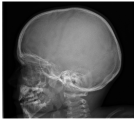
10962.png (64)
d=102.8

10818.png (64)
d=104.0

13505.png (64)
d=105.3

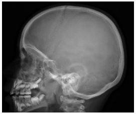
11580.png (64)
d=105.8

15315.png (64)
d=105.9



11800.png (64)
d=106.8

12779.png (64)
d=107.1



Results

Nearest Neighbour (2)

10597.png (22)
d=0.0

17095.png (22)
d=129.0

10054.png (22)
d=139.2

11279.png (22)
d=151.9

11055.png (22)
d=152.9

10229.png (44)
d=154.3

16132.png (21)
d=154.9

18524.png (22)
d=157.2

14198.png (22)
d=157.6

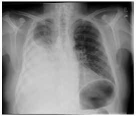
Results
Nearest Neighbour (3)

10246.png (29)
d=0.0

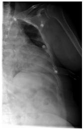
11290.png (29)
d=120.2

15421.png (29)
d=131.6

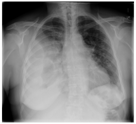
9618.png (108)
d=132.1



10247.png (29)
d=133.8

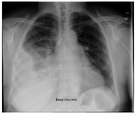


18318.png (108)
d=133.9



18366.png (29)
d=136.4

16951.png (109)
d=136.6



10261.png (111)
d=138.4

Conclusion

- An extension of "bag-of-features" approach
- Novelty: Use of Relational features, and introduction of CCM
- CCMs incorporate elegantly the relative spatial distribution of local features
- Resulting large dimensionality a probable issue

Conclusion

- An extension of "bag-of-features" approach
- Novelty: Use of Relational features, and introduction of CCM
- CCMs incorporate elegantly the relative spatial distribution of local features
- Resulting large dimensionality a probable issue

Thank you for your attention!