

Analysis and Classification of Confocal Laser Endomicroscopic Images to Distinguish Pathological from Healthy Tissue

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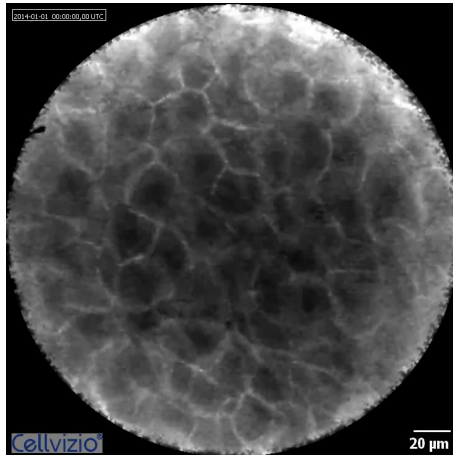


Structure

- Motivation
- Background
- Data & Methods
- Experiments and Results
- Summary & Conclusion

Motivation

Motivation – Initial Problem



Motivation – Initial Problem



Motivation – Cancer of the Oral Cavity

Sixth most common kind of cancer

Problems of diagnosis

- subjectivity of physician
- histological analysis
- surgical resection

Early diagnosis \Rightarrow difficult!

Motivation – Cancer of the Oral Cavity

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Problems of diagnosis

- subjectivity of physician
- histological analysis
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Early diagnosis ⇒ difficult!

⇒ other solutions?

Motivation – Objectives of this Thesis

Overall: separate pathological from healthy images

Benefits:

- objective method to support the physician
- supports diagnosis & finding of the resection site
- time-saving and less harmful for the patient

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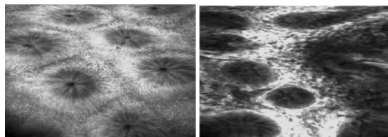
Three problems:

1. creation of image database ⇒ pre-processing ✓
2. annotation of images ⇒ needs to be solved
3. classification of images ⇒ depending on annotation problem

Motivation – State of the Art

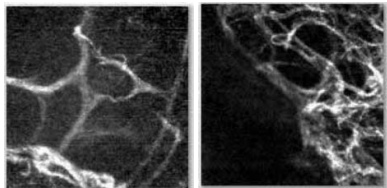
Couceiro et al. [Couceiro, 2012]

- gastrointestinal tract
- arrangement of glands
- Scale Invariant Feature Transform (SIFT)



Désir et al. [Désir, 2012]

- distal lung
- texture description
- Local Binary Patterns (LBP), SIFT

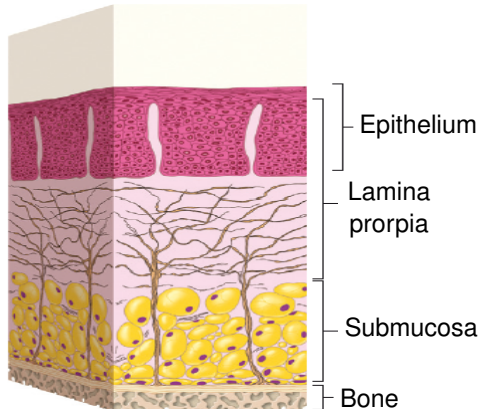


Background

Background – Mucous Membrane

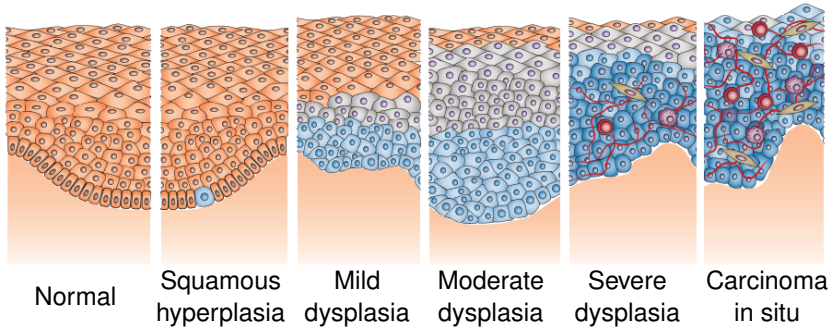
Epithelial layer described by:

- cytology
- architecture

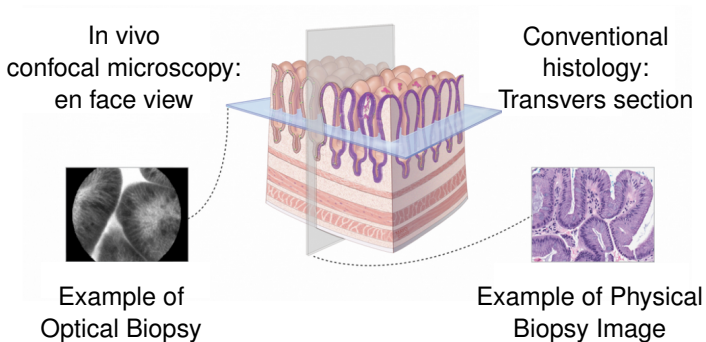


Background – Carcinogenesis

Development stages of oral cancer

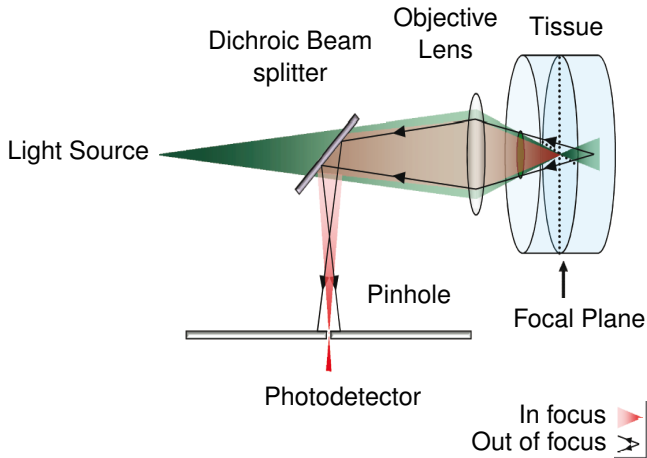


Background – Optical Biopsy



Confocal LaserEndomicroscopy (CLE) allows real time visualization of epithelial layer **in vivo!**

Background – Principle of CLE



Data & Methods

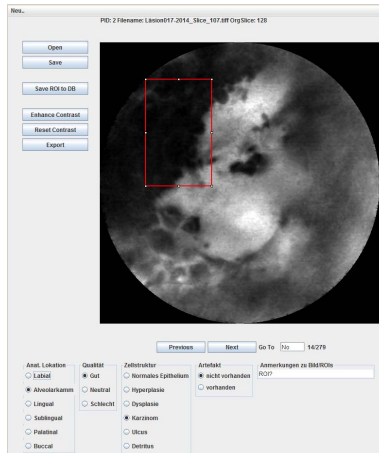
Data – Hardware

Cellvizio Gastro-flex UHD

Imaging rate (frames/s)	12.8
Probe diameter (mm)	2.7
Depth of imaging (μm)	55-65
Lateral resolution (μm)	1
Field of view (μm)	\varnothing 240
Image resolution (px)	576 \times 576



Data – Software

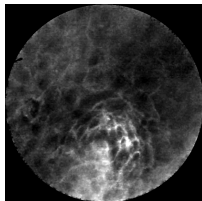


Data – Patient Data

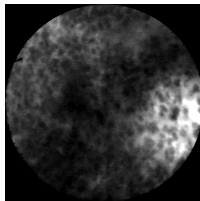
	Control Group	Patient Group
Gender (m/f)	1/-	1/1
Age (years)	30	63.5 ± 2.1

Data – Image Database – Classification Method

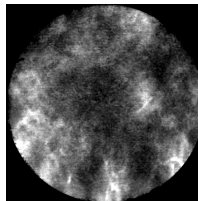
Location	Control	Patient 1	Patient 2
Alveolar Ridge (h/c)	71/-	94/45	41/-
Buccal mucosa (h/c)	-/-	32/15	-/-
Lingual mucosa (h/c)	-/-	-/-	29/27



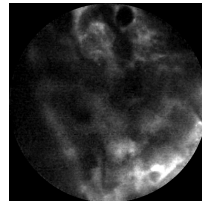
(a) Healthy



(b) Carcinoma



(c) Carcinoma

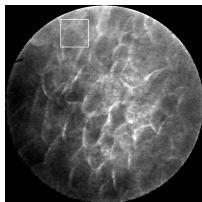


(d) Carcinoma

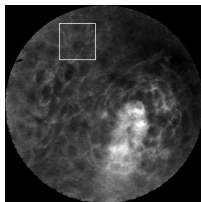
Methods – Classification Algorithm

Subdivide images

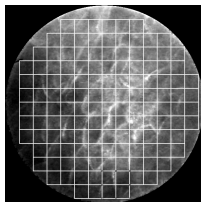
- 110/51 rectangular patches \Rightarrow precalculated coordinates
- sidelength 80/105 px
- step length $0.5 \times$ side length \Rightarrow 50% overlap in x-direction



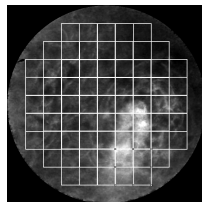
(a) 1×80



(b) 1×105



(c) 110×80



(d) 51×105

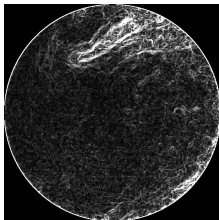
Methods – Extracted Features

Histogram features

- frequency of gray level occurrences of an image
- no information concerning structure or arrangement
- computation of statistics
- 256/512/768 bins

Homogeneity features

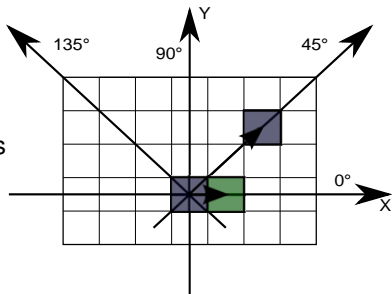
- evaluates gray values
- evaluates edge images
- simple features



Methods – Extracted Features

Grey Level Co-Occurrence Matrices [Haralick, 1973]

- frequency of gray values
- geometrical arrangement of gray values
- different orientation and distances
- lower amount of gray values
- features by Haralick, GLCM (8/16/32 $\text{Im}|\text{gl}$)



Methods – Extracted Features

Local Binary Pattern classical (LBPC) [Ojala, 1996]

- pixel by binary pattern
- binary pattern describe structures
⇒ histogram
- statistical information
- LBPC(R1, N8)

113	176	9
85	100	110
60	30	105

a) 3x3 Image region

1	1	0
0		1
0	0	1

b) Thresholding results

1	2	4
128		8
64	32	16

c) Weighting of Pixels

1	2	0
0	27	8
0	0	16

d) Contribution to pixel

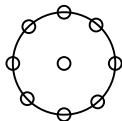
Methods – Extracted Features

Extensions of Local Binary Patterns (LBPr) [Ojala,2002]

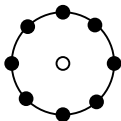
- uniform & rotation invariant
- variable radius & neighborhood
- variable histogram size
- LBPr(R1/2, N8/16)

uniform: \leq two transitions from 1 to 0 or 0 to 1

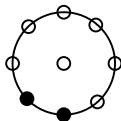
rotation invariant: $LBP_{R,N}^{ri} = \min(\text{ROR}(LBP_{R,N}i))$



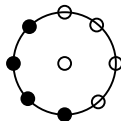
Spot



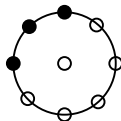
Spot/flat



Line end

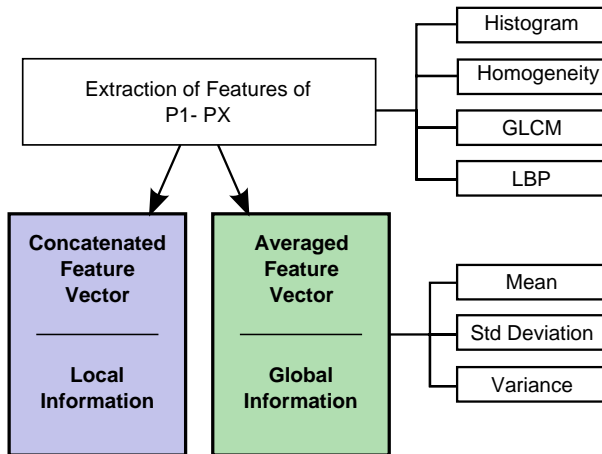


Edge



Corner

Methods – Feature Vectors



Methods – Classifier & Evaluation

Classification algorithms

- Support Vector Machine (SVM)
- Random Forest (RF)
- Bagging (Bag)
- AdaBoostM1 (Ada)

Evaluation methods

- 10-fold crossvalidation
- classification rate (Acc)
- average recall (Rec)

Software

- CONRAD → image analysis & feature extraction
- Weka → classification tasks

Experiments and Results

Experiments – Classification Method

Pathological vs. non-pathological

One patient – same location

- P1 vs. P1 – alveolar ridge
- P1 vs. P1 – buccal
- P2 vs. P2 – lingual

Between subjects – same location

- P1 vs. P2 – alveolar ridge
- P1 vs. P2 & Ctrl – alveolar ridge

All subjects – all locations

Experiments – Classification Method

Pathological vs. non-pathological

One patient – same location

- P1 vs. P1 – alveolar ridge ⇒ Acc/Rec: 100.0% / 100.0%
- P1 vs. P1 – buccal ⇒ Acc/Rec: 100.0% / 100.0%
- P2 vs. P2 – lingual ⇒ Acc/Rec: 100.0% / 100.0%

Between subjects – same location

- P1 vs. P2 – alveolar ridge ⇒ Acc/Rec: 100.0% / 100.0%
- P1 vs. P2 & Ctrl – alveolar ridge ⇒ Acc/Rec: 99.2% / 98.6%

All subjects – all locations ⇒ Acc/Rec: 95.8% / 93.3%

Results – All Subjects all Locations

Concatenated feature vector

Features	Property	Patchsize 51 × 105 concatenated			
		Acc/Rec (SVM) in (%)	Acc/Rec (Ada) in (%)	Acc/Rec (Bag) in (%)	Acc/Rec (RF) in (%)
Histogram	256 bins	81.6/65.4	74.6/50.2	82.8/69.6	83.9/71.9
Histogram	512 bins	80.5/63.8	74.6/50.2	81.6/68.1	83.6/69.4
Histogram	768 bins	80.5/63.4	74.6/50.2	82.2/68.4	85.3/72.4
Homogeneity	—	87.0/74.3	84.2/72.1	86.7/75.3	90.7/82.2
GLCM	8 lmg vl	94.4/92.0	88.1/82.8	88.1/77.4	87.6/75.1
GLCM	16 lmg vl	94.6/92.2	88.4/81.9	87.6/76.6	89.0/78.4
GLCM	32 lmg vl	94.9/92.8	89.3/82.0	88.4/77.6	89.0/78.4
LBPC	R1 N8	78.8/68.1	78.0/58.3	79.9/63.5	81.6/66.5
LBPr	R1 N8	78.8/67.0	81.6/70.0	83.6/71.7	89.0/79.9
LBPr	R2 N16	81.4/68.3	78.0/61.8	83.1/71.7	85.0/74.2

Results – All Subjects all Locations

Concatenated feature vector

Features	Property	Patchsize 110 × 80 concatenated			
		Acc/Rec (SVM) in (%)	Acc/Rec (Ada) in (%)	Acc/Rec (Bag) in (%)	Acc/Rec (RF) in (%)
Histogram	256 bins	83.9/73.8	75.7/57.5	82.2/68.8	84.5/70.7
Histogram	512 bins	84.5/74.6	75.4/53.1	83.3/70.7	84.2/71.3
Histogram	768 bins	84.2/74.0	76.3/57.9	81.6/68.1	85.3/72.1
Homogeneity	—	90.4/82.4	84.7/71.7	89.0/79.9	89.0/78.0
GLCM	8 ImgIvl	95.2/92.6	87.9/79.5	88.4/79.1	87.9/76.4
GLCM	16 ImgIvl	94.9/92.4	89.3/83.6	88.7/78.6	86.4/74.0
GLCM	32 ImgIvl	95.5/93.1	89.0/81.8	89.3/80.5	87.3/75.7
LBPC	R1 N8	84.7/78.7	81.9/70.6	81.4/65.6	81.4/65.9
LBPr	R1 N8	79.7/70.2	80.8/68.7	85.0/74.2	86.4/75.9
LBPr	R2 N16	81.1/70.8	81.9/65.5	85.9/75.1	86.4/74.7

Results – All Subjects all Locations

Averaged feature vector

Features	Property	Patchsize 51 × 105 averaged			
		Acc/Rec (SVM) in (%)	Acc/Rec (Ada) in (%)	Acc/Rec (Bag) in (%)	Acc/Rec (RF) in (%)
Histogram	256 bins	75.4/50.0	76.3/54.0	84.5/73.8	83.6/72.9
Histogram	512 bins	75.4/50.0	75.4/53.1	85.6/75.0	85.9/75.5
Histogram	768 bins	75.4/50.0	75.7/56.0	84.2/72.5	84.5/73.8
Homogeneity	—	79.9/59.2	77.1/56.5	89.3/81.6	90.4/84.3
GLCM	8 Iimglvl	94.9/91.2	93.2/90.9	92.9/89.9	93.5/88.7
GLCM	16 Iimglvl	94.9/91.2	93.5/89.5	94.4/91.2	95.8/93.3
GLCM	32 Iimglvl	94.4/90.1	93.2/89.3	93.8/90.8	94.4/90.1
LBPC	R1 N8	75.4/50.0	76.6/53.1	81.6/67.3	79.1/63.7
LBPr	R1 N8	75.7/51.7	76.6/58.5	83.9/73.1	82.8/71.1
LBPr	R2 N16	76.0/51.1	75.4/51.5	84.7/73.2	84.7/73.2

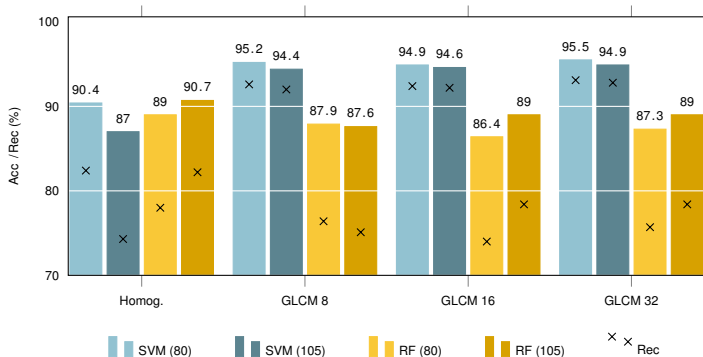
Results – All Subjects all Locations

Averaged feature vector

Features	Property	Patchsize 110 × 80 averaged			
		Acc/Rec (SVM) in (%)	Acc/Rec (Ada) in (%)	Acc/Rec (Bag) in (%)	Acc/Rec (RF) in (%)
Histogram	256 bins	75.4 / 50.0	76.0 / 52.3	84.7 / 75.6	85.0 / 75.4
Histogram	512 bins	75.4 / 50.0	75.1 / 56.0	84.2 / 72.9	83.9 / 73.4
Histogram	768 bins	75.4 / 50.0	76.3 / 54.4	85.0 / 74.2	84.5 / 74.6
Homogeneity	—	79.4 / 58.0	82.2 / 67.7	88.1 / 81.3	92.1 / 85.1
GLCM	8 ImgIvl	94.9 / 91.2	92.7 / 87.4	92.4 / 87.6	94.9 / 91.2
GLCM	16 ImgIvl	94.6 / 91.0	92.7 / 87.4	93.2 / 88.9	94.1 / 89.5
GLCM	32 ImgIvl	94.1 / 90.3	91.2 / 85.7	92.4 / 87.2	94.9 / 90.4
LBPC	R1 N8	75.4 / 50.0	76.6 / 55.8	85.3 / 74.0	81.4 / 69.4
LBPr	R1 N8	76.6 / 53.5	78.8 / 58.8	83.9 / 73.4	82.2 / 71.2
LBPr	R2 N16	77.1 / 53.8	76.6 / 53.1	85.6 / 73.8	84.7 / 74.4

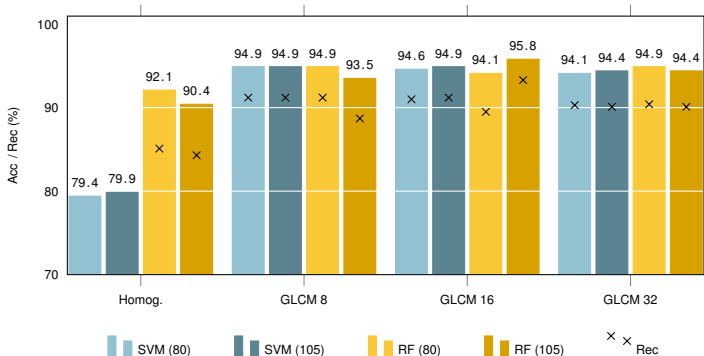
Results – All Subjects all Locations

Comparison of feature vector – concatenated feature vector results



Results – All Subjects all Locations

Comparison of feature vector – average feature vector results



Results – All Subjects all Locations

Confusion Matrix

	H	C
Healthy	262	5
Carcinoma	10	77

Best classification result: 95.8% / 93.3% (avg. RF)

True positive rate

- *Healthy* 98.1 %
- *Carcinoma* 88.5 %

Summary & Conclusion

Summary

- decomposition into individual images
- annotation of images
- classification of pathological from healthy images

Drawbacks

- patient data set
- image database
- correlation of images

Possible improvements

- edge evaluating features
- disease staging
- segmentation of cancer

Conclusion

Objective of this thesis: separate pathological from healthy images

Three problems:

1. creation of image database ✓
2. annotation of images ✓
3. classification of images ✓ **95.8% / 93.3%**

Benefits:

- objective method to support the physician
- supports finding of the resection site
- time-saving and less harmful for the patient

⇒ monitor progress of cancer?

The End