Supervised tissue classification in optical images: towards new applications of surgical data science

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Outline

• Introduction to surgical data science (SDS) for tissue classification
• Aim and research hypotheses of the PhD work
• Hypothesis 1 (H1) – Machine learning provides accurate frame selection
• Hypothesis 2 (H2) – Classification-confidence estimation can improve classification outcomes
• Hypothesis 3 (H3) – Classification outcomes can be further improved with multispectral data
• Hypothesis 4 (H4) – Tissue classification can be integrated in the flow of robot-assisted surgery
• Conclusion
A “physician for all purposes”

Domain knowledge and experience to use all the available information in an optimal manner

Automatic holistic processing of all the available data to facilitate, optimize and objectify care delivery

[Essert et al., 2015, Griffiths et al. 2016, Maier-Hein et al., 2017]
Surgical data science (SDS) → Extracting knowledge from interventional-medicine data
→ Improving the quality of interventional healthcare through the organization, analysis, and modeling of the data

Interventional-medicine workflow

Surgeon's decision process combines:
• Qualitative analysis of patient-specific information from imaging systems and sensors
• Surgeon prior knowledge about medical rules and statistics

[Taylor et al., 2008]
SDS methodology integration allows:

- **Decision-support** (e.g. for assisting the physician when diagnosing patients)
- **Context-awareness** (e.g. for autonomous assistance and collaborative robots)

[Maier-Hein et al., 2017]
Open SDS technical challenges

Aim

Frame sel.

Confidence est.

Multispectral img.

OR integration

Conclusion

3D reconstruction

[Tomasi et al., 2013]

Tissue tracking

[Stoyanov et al., 2012]

Workflow modeling

[Marz et al., 2015]

Intraoperative registration

[Sotiras et al., 2013]

Tissue detection and localization

[Nosrati et al., 2014]

→ Patient’s variability

→ Image variability

→ Acquisition variability
Overview on the current state of SDS for tissue classification

Machine learning (ML) can potentially help in handling variability → The medical domain-specific knowledge can be encoded in a ML-based model through a learning process based on the description of cases solved in the past.

→ Few researches in the medical field
→ Few anatomical regions
→ Few datasets online
→ Poor classification performance

[Kononenko et al., 2001, Kotsiantis et al., 2007, Maier-Hein et al., 2017]
Aim and research hypotheses of the PhD work

Surgical data science challenges
- Decision support and context awareness
- Methodology-reliability improvement
- Integration in the surgical process

Informative-frame selection \( (H1) \)
- Tissue classification + confidence estimation \( (H2) \)
- Extension to multispectral imaging data acquisition \( (H3) \)
- Tissue segmentation + integration within a simulated robot-assisted surgical scenario \( (H4) \)

Frame sel. | Confidence est. | Multispectral img. | OR integration | Conclusion
---|---|---|---|---
Intro | Aim | ABDOMEN | LARYNX | LIVER

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**Informative frame selection** plays a fundamental role:

- Reviewing an endoscopic/microscopy video is a labor-intensive operation [Schuster et al., 2012]
  - Revision time is lowered / The clinician may focus on important clues
- SDS algorithms usually rely on manual frame selection → Frames to be processed show clearly structures of interest
  - The amount of computational power required is lowered / The processing of frames that do not show structures of interest is avoided

**RELATED WORK**

- Random/Uniform frame sampling
- Threshold sensitive
- Requires parameter tuning

[S. Moccia, et al., Computer Methods and Programs in Biomedicine, 2018 - a]
H1: ML supports the selection of informative frames to be processed by tissue classification algorithms

The problem of robust and automatic classification of informative frames is addressed with a focus on laryngoscopy applications.

Major challenges typical of the laryngeal district include:

- Movement of swallowing muscles and vocal fold
- Presence of smooth/wet laryngeal surface
- Varying illumination levels

[S. Moccia, et al., Computer Methods and Programs in Biomedicine, 2018 - a]
H1: ML supports the selection of informative frames to be processed by tissue classification algorithms

New method (M1):
- A new set of features (based on intensity, keypoints, and spatial content)
- Multi-class support vector machines (SVM)

Validation
- 18 narrow-band (NBI) laryngoscopic videos from 18 different patients
- 720 frames labelled (New ground-truth database)
- Three fold cross-validation (patient-level separation)
- Comparison with state of the art (Wilcoxon signed-rank test, \( \alpha = 0.05 \))

[S. Moccia, et al., Computer Methods and Programs in Biomedicine, 2018 - a]
H1: ML supports the selection of informative frames to be processed by tissue classification algorithms

Class-specific recall ($\text{Rec}_{\text{class}}$) for different features with support vector machines (Comparison with the state of the art)

- **Intro**
- **Aim**
- **Frame sel.**
- **Confidence est.**
- **Multispectral img.**
- **OR integration**
- **Conclusion**

10 times faster

Class-specific recall ($\text{Rec}_{\text{class}}$) for different features with support vector machines (Comparison with the state of the art)

- **I**
- **B**
- **S**
- **U**

→ Translation to other anatomical districts

[S. Moccia, et al., Computer Methods and Programs in Biomedicine, 2018 - a]
H2: Reliable tissue classification can be performed by exploiting ML and classification-confidence estimation
Automatic tissue classification plays a fundamental role:

- Diagnostic support
- Context awareness

A strong literature on automatic classification exists:

- Hand-crafted / Learned features
- Supervised machine-learning / Deep learning approaches

How do we know if we can trust the classification outcome?

A new method (M2) have been developed to encode classification confidence estimation. The M2 was tested on:

1. Laryngeal tissue classification in narrow—band imaging (NBI) endoscopy
2. Hepatic tissue classification in RGB images acquired with smartphones in the OR

[Esteva et al., 2017, Maier-Hein et al., 2017, Poplin et al., 2018]
Early-stage laryngeal cancer diagnosis is of primary importance for lowering patient’s mortality or morbidity.

Major challenges typical of the laryngeal district include:

• Small alterations of the mucosal surface
• Specular reflections/Varying illumination levels
• High patient’s variability

**RELATED WORK**

• Threshold sensitive
• Requires parameter tuning

[Poels et al., 2003, Barbalata et al., 2016]

[S. Moccia, et al., Journal of Medical Imaging, 2017]
H2: Reliable tissue classification can be performed by exploiting ML and classification-confidence estimation

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**New method (M2):**
- Textural and intensity features
- Multi-class support vector machines (SVM)
- 4 tissue classes:
  1. Tissue with IPCL-like vessels (IPCL)
  2. Leukoplakia (Le)
  3. Tissue with hypertrophic vessels (Hbv)
  4. Healthy tissue (He)
- Confidence estimation (Gini’s coefficient)
Class-specific recall ($\text{Rec}_{\text{class}}$) for different features with support vector machines

Stat$_1$: Intensity mean, variance and entropy

$F_{\text{GLCM}}$: Gray-level co-occurrence matrix

$H_{\text{LBP}}$: Histogram of local binary pattern

Including a measure of confidence on classification outcomes helps improving $\text{Rec}_{\text{class}}$

$\tau$: Threshold on the confidence value

[S. Moccia, et al., Journal of Medical Imaging, 2017]
Comparison of confusion matrices

H2: Reliable tissue classification can be performed by exploiting ML and classification-confidence estimation

**Aim**

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**Intro**

- [Barbalata et al., 2016]
- SVM-based classification
- Confidence estimation

- [S. Moccia, et al., Journal of Medical Imaging, 2017]

**Figure Description**

- [Comparison of confusion matrices]
- He: Healthy tissue
- Hbv: Hypertrophic blood vessels
- Le: Leukoplakia
- IPCL: Abnormal IPCL-like vessel
Hepatic steatosis (HS) is one of the most important donor characteristic that can influence graft function and so liver transplantation outcome [Koneru et al., 2002].

Major challenges typical of the laryngeal district include:

• Limited time availability for diagnosis
• Small alterations of the liver surface
• High patient’s variability

RELATED WORK

• Threshold sensitive
• Requires additional imaging instrumentation
• Only correlates physical characteristics with HS level

H2: Reliable tissue classification can be performed by exploiting ML and classification-confidence estimation

Method M2

Validation
- 40 images acquired with smartphones in the operating room (relative to 40 different donors)
- 20 images (300 patches) from accepted donor’s graft
- 20 images (300 patches) from rejected donor’s graft
- One-patient-out cross-validation (patient-level separation)
H2: Reliable tissue classification can be performed by exploiting ML and classification-confidence estimation

Confusion matrices for patch classification with different features

**Stat**₁: intensity mean, variance and entropy

**F\textsubscript{GLCM}:** gray-level co-occurrence matrix

**H\textsubscript{LBP}:** Histogram of local binary pattern

**Stat**₁ + **H\textsubscript{LBP}

**F\textsubscript{GLCM}**

**H\textsubscript{LBP}

Visual confusion matrix

NT: Non-transplanted

T: Transplanted

**New method (M2.1):**

- Textural, intensity features and **blood features**
- **Semi-supervised approach:** Support vector machines (SVM) – Single instance learning (SIL)

→ Steatosis is not homogeneous in the hepatic tissue
H2: Reliable tissue classification can be performed by exploiting ML and classification-confidence estimation

Aim
Frame sel. Confidence est. Multispectral img. OR integration Conclusion

SVM + Clustering

SVM - SIL

True label
NT: Non-transplanted
T: Transplanted

Predicted label

Misclassified patches
H3: Tissue classification with ML and confidence estimation can be further improved by using MI data.

Aim

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Extension to multispectral imaging data acquisition (H3)

Tissue segmentation + integration within a simulated robot-assisted surgical scenario (H4)
In parallel to the development of new computer-assisted strategies to tissue classification, the imaging field is also evolving thanks to new technologies such as **multispectral imaging** (MI) [Li et al., 2013].

- MI enables us to capture both **spatial** and **spectral** information on structures
- Images with dozens of channels
- MI can potentially reveal better tissue-specific optical characteristics

**RELATED WORK**

- Threshold sensitive
- Require parameter tuning
- Ex vivo analysis

[S. Moccia, et al., IEEE Transaction on Biomedical Engineering, 2018]
H3: Tissue classification with ML and confidence estimation can be further improved by using MI data

New method (M3):
- Textural and intensity features
- Superpixel segmentation
- Multi-class support vector machines
- Multispectral data acquisition

Aim
Frame sel.
Confidence est.
Multispectral img.
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Data acquisition and pre-processing
Feature extraction
Superpixel-based classification
Confidence estimation

Superpixel n:
Abdominal wall
Liver
Spleen
Gallbladder
Diaphragm
Intestine

Confident
gallbladder
Confident
liver
Non-confident
diaphragm

Tagging result:
Liver
Gallbladder

- 7 MI frame sequences from 7 different pigs
- 60 frames (New ground-truth database)
- 6 tissue classes:
  a) Abdominal wall
d) Gallbladder
  b) Liver
e) Diaphragm
c) Spleen
f) Intestine
- Comparison with standard RGB images (Wilcoxon signed-rank test, $\alpha=0.05$)

[S. Moccia, et al., IEEE Transaction on Biomedical Engineering, 2018]
Class-specific superpixel classification accuracy \( (\text{Acc}_{\text{Spx}}) \) for different threshold \( (\tau) \) on the confidence measure.

The confidence measure helps in excluding superpixels affected by noise, specular reflection, partial organ effect and movement.

[S. Moccia, et al., IEEE Transaction on Biomedical Engineering, 2018]
H4: ML-based tissue segmentation can be integrated in the flow of a simulated robot-assisted surgery to provide region avoidance.

**Aim**

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The use of robotic systems for interventional healthcare has rapidly increased during the last decade. [Alemzadeh et al., 2016].

Nowadays, research in robotic systems aims at improving the execution of interventional procedures through providing tremor compensation and **virtual-fixture forbidden-region avoidance** [Taylor et al., 2008].

Indeed, by selecting regions to be preserved (such as healthy tissues, vessels, nerves) the robot can be prevented to enter such regions, reducing risks related to tissue damaging due to tool misplacement.

→ **Automatic tissue classification can be integrated in robot-assisted surgery to provide context awareness and support the surgeon in avoiding sensitive structures**

[S. Moccia, et al., Annals of Biomedical Engineering (under minor revision)]
[S. Moccia, et al., Computer Methods and Programs in Biomedicine, 2018 - b]
During neurosurgery procedures, surgeons perform accurate and minute operations with limited visibility

[Morita et al., 2005]

**New method (M4):**

- Deep learning for vessel segmentation
- Virtual-fixture control

[H4: ML-based tissue segmentation can be integrated in the flow of a simulated robot-assisted surgery to provide region avoidance]

[S. Moccia, et al., Annals of Biomedical Engineering (under minor revision)]

[S. Moccia, et al., Computer Methods and Programs in Biomedicine, 2018 - b]
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**M4: U-net for vessel segmentation**

[Ronneberger et al., 2015]

**M4: Distance-based virtual fixture control**

\[ \mathbf{p}_{\text{rest}} \]

\[ \mathbf{p}_{\text{closest}} \]

\[ d < d_{\text{safety}} \]

- \( \mathbf{p}_{\text{rest}} \): Micron tip rest position
- \( d \): Vessel-Micron tip distance
- \( d_{\text{safety}} \): Safety distance from vessel
- \( \mathbf{p}_{\text{closest}} \): Closest vessel point to Micron

**H4: ML-based tissue segmentation can be integrated in the flow of a simulated robot-assisted surgery to provide region avoidance**

[S. Moccia, et al., Annals of Biomedical Engineering (under minor revision)]

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Classification $DSC = 96\%$

Classification $DSC = 81\%$

Raw

Gold standard

Outcome

Phantom vessels

Real vessels

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[Z. Moccia, et al., Annals of Biomedical Engineering (under minor revision)]

[Z. Moccia, et al., Computer Methods and Programs in Biomedicine, 2018 - b]

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Future perspectives:

- Building larger datasets for training and evaluation
- Building shared platforms for algorithm testing and image labeling
- Integrating with tracking/3D reconstruction/registration/…
- Testing in the actual clinical practice
THANK YOU!
01/05/2015 – 30/04/2018
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01/05/2015 – 30/04/2018