Superpixel-based Segmentation and Classification of Gastrointestinal Landmarks and Diseases

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Presentation Outlines

- Introduction
- Objectives
- Block diagram of Proposed System
- Methodology
- Results
- Discussion and Conclusions
- Future works
- References
The GI tract can be affected by different kinds of diseases such as:

- Ulcer
- GI inflammation
- Cancer
- Crohn’s disease and etc.
Introduction: Diseases affecting GI tract

Figure 1: Various normal and abnormal images captured by wireless capsule endoscopy (WCE) (A), (B) bleeding images; (C), (D) ulcer images; (E), (F) tumor images; (G), (H) WCE normal images [1]
Introduction: Diagnosis of GI diseases

- Endoscopy is a Gold standard
- The most commonly used Endoscopy are:
  - Gastroscopy
  - Colonoscopy
  - wireless capsule endoscopy (WCE)

Figure 2: (A) Gastroscopy (B) Colonoscopy  (C) WCE

Source: https://www.researchgate.net/publication/311623416/figure/fg6/AS:668590902628382@1536415901999/Schematic-diagram-during-gastrointestinal-endoscopy-a-Gastrointestinal-endoscope-b.png
Introduction: Problem Statements

- During endoscopy, approximately more than 10K endoscopic frames are produced, depending on the target GI area.
- Physicians require a substantial amount of time to review those frames.
- The review process could be laborious and time-consuming. Besides, it is prone to human errors.
- Difficulty of detecting small polyps and flat lesions.
- Lack of widespread expertise.
- Therefore, an objective and automated decision support system would be highly welcomed.
The Objectives

➢ To illustrate how superpixel methods can be used to segment and classify various GI diseases and landmarks of endoscopic images.

➢ To compare classification results of superpixel-based methods with pixel-based one by using several performance evaluation metrics.

➢ To evaluate and compare the segmentation performance of superpixel methods on polyp images with the ground truth mask.
Figure 3: A block diagram of the proposed computer-aided diagnosis system for detection and classification of the GI diseases and landmarks.
The following will be covered under this section:

- Used Datasets
- Superpixel Segmentation
- Feature Extraction
- Classification
We evaluated our work on two datasets, namely:

Used dataset 1: Kvasir Dataset v2 (2017)

- Contains 8,000 GI images, 8 classes, 1,000 images for each class.
  - Esophagitis
  - Polyps
  - Ulcerative Colitis
  - Z-line
  - Pylorus
  - Cecum
  - Dyed and Lifted Polyps
  - Dyed Resection Margins
The **Kvasir Dataset v2(2017)** were divided into three binary classification problems:

- **Upper GI (Esophagitis and Normal Z-Line)**
- **Middle GI (Polyps and Normal Pylorus)**
- **Lower GI (Ulcerative Colitis and Normal Cecum)**
Used dataset 2: Kvasir-SEG dataset

- **Kvasir-SEG Dataset (2020):**
  - consists of 1000 annotated polyp images with their respective ground truth masks

![Sample polyp images and their corresponding masks from the Kvasir-SEG dataset](image)

Figure 4: Sample polyp images and their corresponding masks from the Kvasir-SEG dataset
Superpixel segmentation

Definition of Superpixel:

- Cluster of connected pixels with similar features (e.g. color, brightness, texture...).

Figure 5: Superpixel Segmentation of GI image (Normal Z-line)
Simple linear iterative clustering (SLIC)

- Proposed by Achanta et al. in 2012 [4].
- Adaptation of the well-known $k$-means segmentation method
- Each pixel of an image is represented by a 5D feature vector composed of the values of the,
  - $(l, a, b)$ color components and
  - $(x, y)$ pixel coordinates.

Figure 6: (a) standard $k$-means searches the entire image. (b) SLIC searches a limited region.
The following features were extracted from generated superpixels:

- Local binary patterns (LBP)
- Gray Level Co-occurrence Matrix (GLCM)
- First Order Statistical (FOS) features
Specifically, GLCM and FOS features were extracted from:

- 5 image channels (red, green, blue, hue, and gray-scale channels)
- LBP map associated with the gray-scale image.

So, the overall number of features are (18 GLCM features + 4 FOS features) \times 6 channels + 36 LBP histogram features = 168 features.

From now on, we assigned:

- \textbf{mGLCM} to indicate the multichannel GLCM the features extracted from the aforementioned six image channels.
- Similarly, \textbf{mFOS} for indicating the multichannel FOS features
In our experiments, an support vector machine (SVM) classifier was used to classify the superpixels using the extracted features.

An SVM binary classifier with a polynomial-type kernel was employed.

Figure 7: Illustration of different hyper-planes. $H1$ separates the two classes with a small margin, whereas $H2$ separates them with the maximum margin.
Evaluation metrics

➢ The following measures were computed for evaluating the classification output,
  ✓ Accuracy
  ✓ Recall
  ✓ Area under the ROC curves (AUC)

➢ For evaluating the segmentation output:
  ✓ Dice Similarity Coefficient (DSC)
  ✓ Intersection over Union (IoU) were computed.
This section provides:
1. Classification of GI images with different feature combinations
2. Comparative evaluation against ground-truth polyp segmentation
Results: Classification of GI images with different feature combinations

<table>
<thead>
<tr>
<th>Features</th>
<th>upper GI part (K=10)</th>
<th>middle GI part (K=15)</th>
<th>lower GI part (K=20)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>pixel-based</td>
<td>superpixel-based</td>
<td>pixel-based</td>
</tr>
<tr>
<td></td>
<td>acc</td>
<td>rec</td>
<td>AUC</td>
</tr>
<tr>
<td>LBP</td>
<td>62.33</td>
<td>62.50</td>
<td>65.85</td>
</tr>
<tr>
<td>mFOS</td>
<td>68.50</td>
<td>70.63</td>
<td>76.6</td>
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<tr>
<td>mGLCM</td>
<td>70.17</td>
<td>69.58</td>
<td>77.54</td>
</tr>
<tr>
<td>LBP-mFOS</td>
<td>71.33</td>
<td>73.77</td>
<td>76.10</td>
</tr>
<tr>
<td>LBP-mGLCM</td>
<td>69.67</td>
<td>70.34</td>
<td>75.85</td>
</tr>
<tr>
<td>mFOS- mGLCM</td>
<td>69.83</td>
<td>69.90</td>
<td>76.62</td>
</tr>
<tr>
<td>LBP-mFOS-mGLCM</td>
<td>70.00</td>
<td>70.83</td>
<td>75.38</td>
</tr>
</tbody>
</table>

Figure 8: Classification results for the landmarks and diseases of the upper, middle, and lower GI parts with the superpixel-based and pixel-based methods.
Results: ROC Analysis (Upper GI)

Figure 9: ROC curves of the upper GI classification problem with the LBP-mFOS-mGLCM features.
Figure 10: ROC curves of the middle GI classification problem with the LBP-mFOS features.
Figure 11: ROC curves of the lower GI classification problem with the LBP-mGLCM features.
Results: Comparative evaluation against ground-truth polyp segmentation

We followed a series of steps to get specific locations of the polyps.

✓ Computation of segmentation maps at various superpixel levels
✓ Calculating the Dice similarity coefficient (DSC) for each generated superpixel with respect to its respective ground truth mask
✓ Finally, a superpixel with the highest DSC value was considered to be polyp object
Comparative evaluation against ground-truth polyp segmentation

We used 80 images of both small and large polyps for qualitative comparisons of the SLIC segmentation method.

Figure 11: Visual comparison of superpixel-based polyp segmentation methods: (a) original images, (b) ground truth maps, (c) SLIC-based segmentation outputs.
Comparative evaluation against ground-truth polyp segmentation

Table 1: Mean DSC and IoU values of SLIC-based segmentation method.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Large Polyps</th>
<th>Small polyps</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSC</td>
<td>0.8475±0.0538</td>
<td>0.7631±0.058</td>
</tr>
<tr>
<td>IoU</td>
<td>0.7388±0.0772</td>
<td>0.62±0.074</td>
</tr>
</tbody>
</table>
Quantitatively, the experimental results showed that \textit{superpixel-based} GI images classification methods outperformed the \textit{conventional pixel-based} ones.

The SLIC-based segmentation method was generally found to perform better in segmenting large polyp compared to that of small ones.
Superpixel methods have different parameters that control the segmentation output.

- they could directly or indirectly affect the segmentation results.
- it is important to optimize these parameters according to the classification problem at hand.
Future works

In the future, we aim:

- to conduct further comparisons with other superpixel methods
- to combine superpixel and deep learning methods for the classification of GI diseases and landmarks
- to perform a more detailed analysis of superpixels such as fine-tuning segmentation control parameters that could affect segmentation output.


Thank you!!!

Questions?