Tissue classification for laparoscopic image understanding based on multispectral texture analysis

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ABSTRACT

Intra-operative tissue classification is one of the prerequisites for providing context-aware visualization in computer-assisted interventions. As many anatomical structures are difficult to differentiate in conventional RGB medical images, we propose classification based on multispectral image patches. In a comprehensive ex-vivo study we show (1) that multispectral imaging data is superior to RGB data for organ tissue classification when used in conjunction with widely applied feature descriptors and (2) that combining the tissue texture with the reflectance spectrum can improve the classification performance. Overall, our study suggests that multispectral imaging data can be used for accurate organ classification in computer-assisted endoscopic interventions.

Keywords: tissue classification, multispectral laparoscopy, multispectral texture analysis

1. PURPOSE

In contrast to traditional open surgeries, laparoscopy is less invasive, causing smaller incisions and providing shorter recovery periods. However, monitoring the surgery status is difficult as the intra-operative vision provided by the laparoscope is usually limited. To obtain semantic interpretation of the surgical scene and provide effective guidance in computer-assisted interventions, an accurate tissue classification method is desirable.

Laparoscopic image understanding based on tissue classification has been investigated in recent years.\textsuperscript{1} More recently, multispectral (or hyperspectral) imaging techniques have achieved success in cancer detection and tissue classification.\textsuperscript{2} Multispectral images generally have tens or hundreds of channels, each of which corresponds to the reflection of light within a certain wavelength band. Therefore they can provide high spectral resolution and reveal optical tissue characteristics. Tissue classification methods so far in the literature mainly use the image pixel, which corresponds to a reflectance spectrum at a specific position, as the feature descriptor.\textsuperscript{3,4} We expect that tissue classification methods can be further improved by incorporating texture information, as they have been already successfully applied to cancer detection.\textsuperscript{5,6}

In this paper, we conduct a comprehensive study of tissue classification for laparoscopy based on multispectral texture analysis. We aim to show that multispectral imaging techniques can be used for accurate organ tissue classification for laparoscopy.
To our knowledge, we are the first to investigate the problem of tissue classification based on multispectral texture analysis for intra-operative laparoscopy. The contribution of this paper is three-fold: (1) We perform a comprehensive ex-vivo study and show that the multispectral image is superior to RGB for tissue classification in the laparoscopic scene. (2) We propose a feature descriptor which combines texture and spectral information. This novel descriptor outperforms other conventional methods. (3) Instead of capturing a large number of bands, we show that tissue classification is also possible with a small but discriminative subset, which speeds up the imaging time for in-vivo laparoscopy. Our experiments suggest that multispectral imaging techniques can be used for accurate tissue classification in computer-assisted interventions.

3. MATERIALS AND METHODS

In this paper, we discriminate four types of porcine organ tissues typically encountered during hepatic laparoscopic surgeries: liver, gallbladder, colon and kidney, which are collected from three individual pigs. As illustrated in Figure 1, the tissue classification workflow in this paper consists of three steps: (1) image acquisition, (2) preprocessing and (3) classification.

3.1 Image Acquisition

Multispectral images are captured using a custom built multispectral laparoscope. It combines a Richard Wolf (Knittlingen, Germany) laparoscope and light source with the 5Mpixel Pixelteq Spectrocam (Largo, FL, USA). According to Wirkert et al., the selected light filters have central wavelengths of 470 nm, 480 nm, 511 nm, 560 nm, 580 nm, 600 nm, 660 nm and 700 nm. The camera runs at 20 fps.

When capturing images, the light is only provided by the laparoscopic light source. We target the rod lens to a smooth region of each organ whose mean surface normal is approximately perpendicular to the horizontal plane and capture images by varying the camera pose. The camera pose is defined by \((\theta, d)\), where \(\theta\) is the angle between the distal tip of the rod lens and the horizontal plane and \(d\) is the distance between the lens tip and the organ surface. Other degrees of freedom are not considered, as they provide trivial differences in the image. We specify \((\theta, d) = \{30^\circ, 60^\circ, 90^\circ\} \times \{4cm, 5.5cm, 7cm\}\), as these distances and angles are typically encountered during laparoscopic surgeries. Therefore, we obtain an image set containing 27 subsets denoted by \((\text{pig}_i, \theta_j, d_k) = \{\text{pig}_1, \text{pig}_2, \text{pig}_3\} \times \{30^\circ, 60^\circ, 90^\circ\} \times \{4cm, 5.5cm, 7cm\}\), in which the images have diverse anatomical structures and illumination conditions.

As the camera does not provide RGB images directly, we select the channels of 470 nm, 560 nm and 700 nm and regard them as blue, green and red.

3.2 Preprocessing

Image preprocessing involves noise removal, ground truth annotation and image cropping. Image is restored using Total Variation, which is a typical method for removing Gaussian noise. Due to infeasible regions such as exposure caused by specular reflection, we annotate the available regions in the image and assign a label to the imaged tissue. Based on the annotation, the image is cropped into several patches of size 300 \(\times\) 300 by pixel and 100 patches are selected randomly and stored in the dataset \(S\). Consequently, the dataset \(S\) is perfectly balanced. It contains 27 subsets, each subset contains four organ tissue classes and each class contains 100 image patches. Figure 2 shows some samples in \(S\).
3.3 Classification

Firstly, we extract the feature vector of each image patch. In this paper, we use Grey-Level Co-occurrence Matrix (GLCM), Gabor Filter Bank (GFB) and Local Binary Pattern (LBP) to extract texture information and use the averaged spectrum (AS) to extract spectral information. In addition, we concatenate the feature vectors of LBP and AS and propose a novel feature descriptor (AS+LBP), which can be regarded as a combination of texture and spectral information. To compensate for motion artifacts which typically happen during surgeries, the feature vector of each image channel is separately extracted and concatenated. To improve the robustness against light variation, we normalize both the feature vectors of individual channels and the feature vector of the entire patch.

Secondly, a one-against-one multi-class support vector machine (SVM) with a Gaussian kernel is applied to discriminate tissues, whose model hyper-parameters are optimized via grid search and cross validation. The classification performance is evaluated using cross-validation on the dataset and measured by the accuracy rate, which is the ratio of correctly classified samples to all samples in the testing set.

4. EXPERIMENTS AND RESULTS

The classification test is performed on every subset of \( S \) in turn, i.e. when the performance is tested on \((\text{pig}_i, \theta_j, d_k)\), the classifier is trained on \( \{(\text{pig}\_i', \theta_j', d_k') | i' \neq i\} \). Thus, we obtain overall 27 accuracy rates and create a box plot to show them in the first row of Figure 3.

To test the influence of camera pose changes, we exclude the camera pose in the testing set from the training set. Specifically, when testing on \((\text{pig}_i, \theta_j, d_k)\), the classifier is trained on \( \{(\text{pig}\_i', \theta_j', d_k') | i' \neq i, j' \neq j, k' \neq k\} \). The accuracy rates are shown in the second row of Figure 3.

5. DISCUSSION

Comparing the two box plots in each row of Figure 3, the performance using the multispectral imaging data is better than the performance using the RGB imaging data for all feature descriptors except GFB. This fact shows that using multispectral imaging data can benefit tissue classification in general. A probable reason for the weak performance of GFB is that the means and the standard deviations of GFB responses are not sufficiently robust to illumination changes. Also note that our synthetic RGB image contains more specific information than a real RGB image, as it is composed of bands with a Full Width Half Maximum of 20nm, thus being much narrower than real RGB bands. We conjecture that real RGB images perform worse.

When excluding the camera pose used in the testing data from the training data, all performances deteriorate simultaneously. This may be caused by two reasons: (1) Excluding the camera pose from the training dataset decreases the number of samples for training and (2) the feature descriptors are not fully invariant to camera pose changes. Also, this result indicates that the robustness to camera pose changes is mainly provided by the training data rather than the feature description methods.

\*These three texture representation methods are implemented based on the Python module scikit-image.

\†The SVM classification and hyper-parameter selection are implemented based on the Python library scikit-learn.
In each box plot of Figure 3, the proposed feature descriptor AS+LBP performs best. This result shows that combining texture information and spectral information improves laparoscopic tissue classification.

6. FUTURE WORK AND CONCLUSION

In future work we aim to collect more data in order to improve the robustness of the feature descriptor to camera pose changes. Additionally we plan to perform live intra-operative tissue classification on in-vivo data, while the classifier will be trained using ex-vivo data. In this case, we will use domain adaptation methods to compensate for shifting appearances and biological properties.

In conclusion, this paper provides a comprehensive study of tissue classification based on multispectral texture analysis. According to our experiments, we show that the multispectral image is superior for tissue classification compared to the RGB image. Based on the multispectral image with eight bands, the novel feature descriptor combining texture and spectral information achieves the best performance. Therefore, we suggest that using multispectral imaging data is beneficial for organ tissue classification in laparoscopy.

REFERENCES