

SIFT Key-Points for Lung Tumor Detection in PET/CT Images

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Abstract

Automatic tumor segmentation enables a fast, reliable and reproducible diagnostic to deliver best treatment procedures for cancer patients. However, state-of-the-art tumor segmentation algorithms are based on manual input which is time- and work-consuming. Furthermore, varying inputs can lead to different segmentation results. To simplify the workflow, a tumor detection algorithm should be used instead of manual input. In this preliminary study, a tumor detection algorithm was investigated and validated for six PET/CT data sets of lung tumor patients. Scale-invariant feature transform (SIFT) keypoints were extracted as tumor candidates in PET images. For each candidate point, intensity, scale and orientation invariant features were calculated both from the PET images and registered CT images. Based on these features, the keypoints were classified either as tumor or as background with a neural network. The neural network classification showed an AUC of 0.71. The tumor detection ratio was 78.6 %. The result of the evaluation with clinical data demonstrated the high potential of the presented lung tumor detection algorithm. We are convinced, further developments of this approach will result in enhanced cancer detection in the entire body.

Introduction

Motivation

- In 2016, the American Cancer Society estimated approximately 1,685,210 new cancer cases [1].
 - **Early and reliable cancer diagnosis is required.**
- Tumor segmentation algorithms
 - Based on manual input which is time- and work-consuming
 - Varying input can lead to different segmentation results
 - **Tumor detection algorithm is required.**
- Variability of the standardized uptake value (SUV) in PET images [2].
 - **Intensity independent approach is required.**

Idea: Use intensity, scale and orientation invariant features at keypoint locations

Methods

A cell detection algorithm of Mualla et al. [3] was completely adapted for lung tumor detection in registered PET/CT volumes (see Fig. 1). For evaluation a leave-one-out cross validation was performed with six clinical data sets (see Fig. 2).

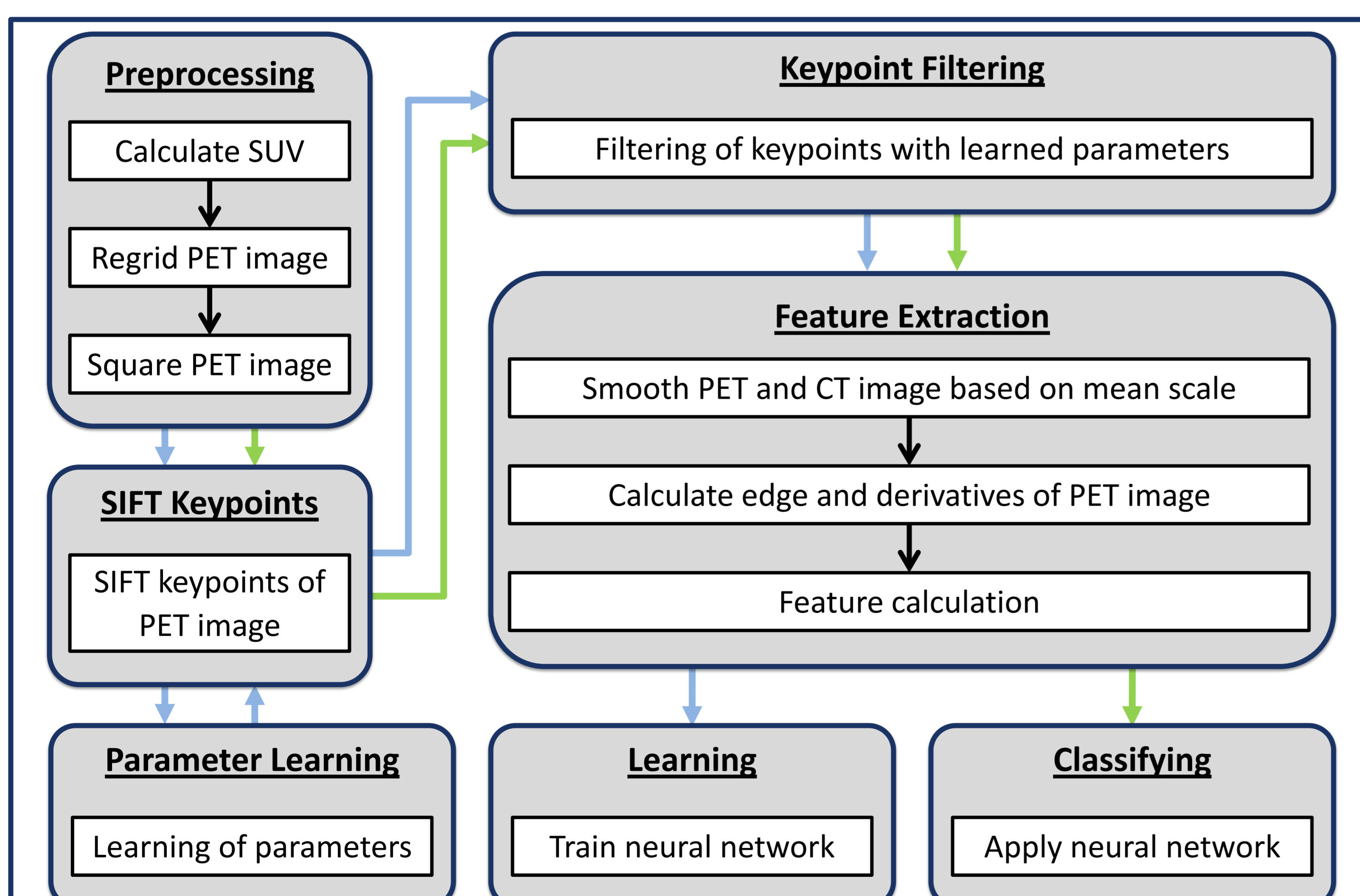


Figure 1: Flowchart of the detection framework. The learning algorithm is depicted with blue arrows. The green arrows show the detection process.

Results

Decision boundary

- Results are presented exemplarily for a threshold of 0.5015.

Overall classification result (see Fig. 3a)

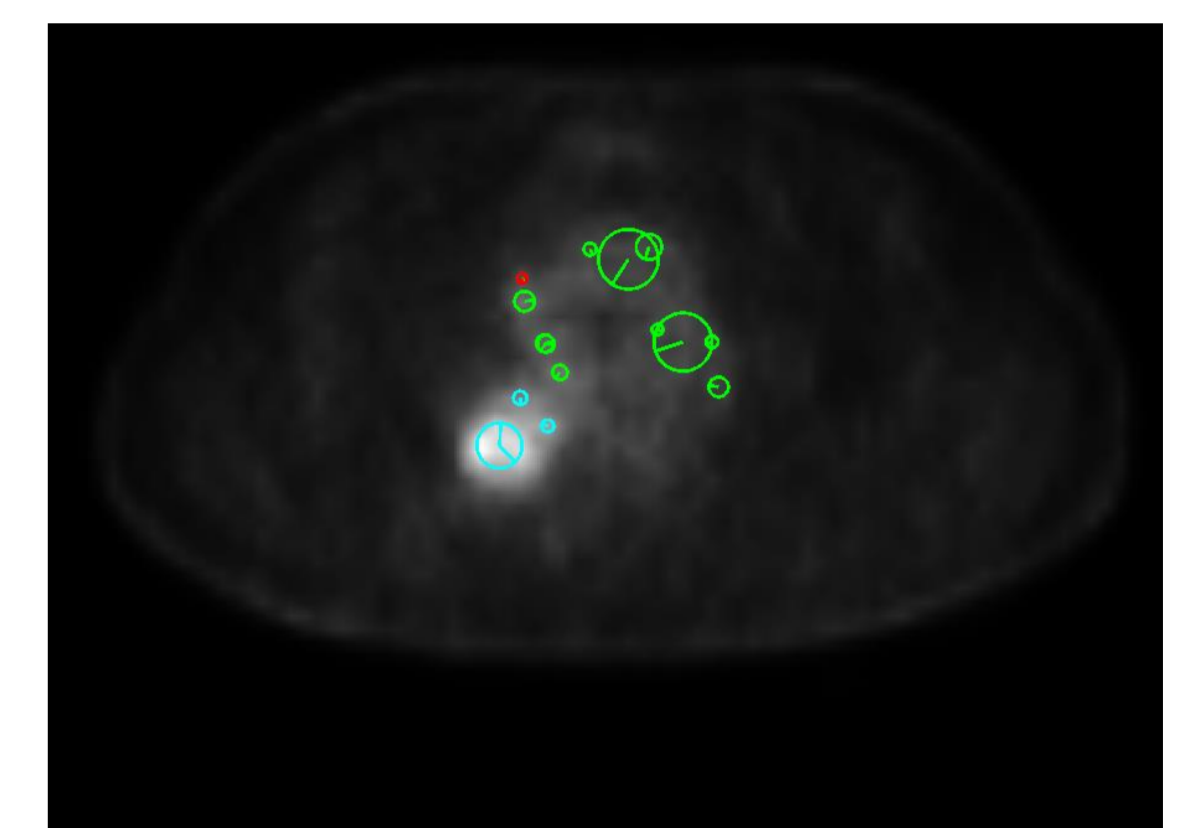
- Sensitivity: 70.4 %
- Specificity: 65.6 %
- Area under the curve: 0.71

Overall detection result (see Fig. 3b)

- Tumor detection ratio: 78.6 %
- False alarm ratio: 98.2 %



(a) CT image



(b) PET image with result

Figure 2: Slice through the heart. Keypoints are displayed as circle. Green: true negative; Blue: true positive; Red: false positive.

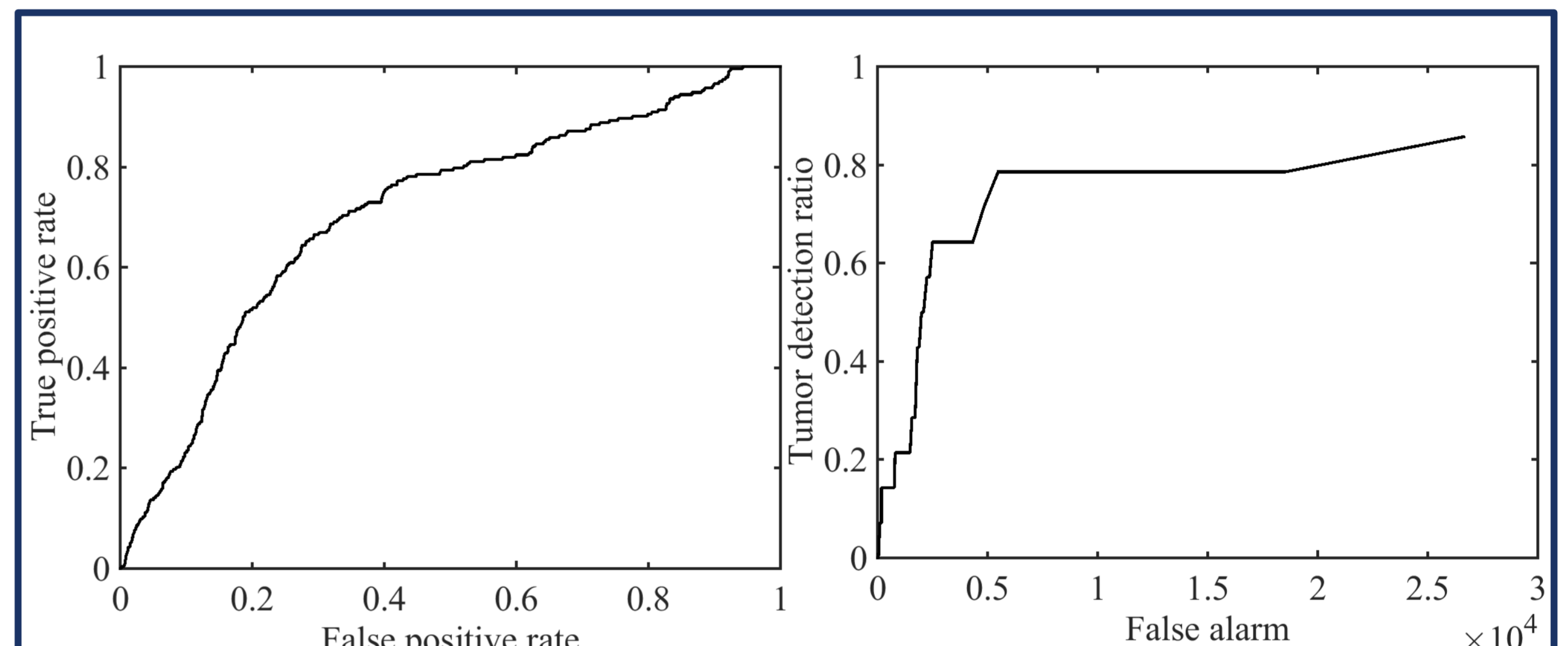


Figure 3: ROC curve analysis for all images. (a) Standard ROC curve which describes the classification performance. (b) ROC-like curve to describe the performance of the tumor detection.

Discussion and Conclusion

Classification result

- Our selected features and the neural network are suitable to separate background from tumor keypoints.
- Possible improvements: 3D features, more training data

Detection result

- Invariant features for SIFT keypoints classified by a neural network have a high potential for lung tumor detection.
- High false alarm ratio is not reasonable.
- Possible improvement: 3D SIFT keypoint extraction

Conclusion

SIFT keypoints in combination with neural network classification have a great potential for lung tumor detection in PET/CT. However, for clinical use, further developments are necessary.

References

- [1] American Cancer Society: Cancer Facts & Figures 2016.
- [2] S.C. Huang, Nucl. Med. Biol. 27(7):643-646, 2000.
- [3] F. Mualla et al., IEEE Trans. Med. Imag. 32(12):2274-2286, 2013.