

Chapter 68

Automatic Organ Localization on X-Ray CT Images by Using Ensemble-Learning Techniques

Xiangrong Zhou
Gifu University, Japan

Hiroshi Fujita
Gifu University, Japan

ABSTRACT

Location of an inner organ in a CT image is the basic information that is required for medical image analysis such as image segmentation, lesion detection, content-based image retrieval, and anatomical annotation. A general approach/scheme for the localization of different inner organs that can be adapted to suit various types of medical image formats is required. However, this is a very challenging problem and can hardly be solved by using traditional image processing techniques. This chapter introduces an ensemble-learning-based approach that can be used to solve organ localization problems. This approach can be used to generate a fast and efficient organ-localization scheme from a limited number of training samples that include both original images and target locations. This approach has been used for localizing five different human organs in CT images, and the accuracy, robustness, and computational efficiency of the designed scheme were validated by experiments.

INTRODUCTION

In this chapter, we provide an overview of a machine-learning-based localization approach. First, we discuss the background of the automated organ localization methods in computed tomography (CT) imaging. Because this is a large topic,

we focus only on the ensemble-learning-based approach. Second, we give a technical overview of our approach (Zhou, 2010) as an example and describe in detail the steps involved in this approach. Third, we describe the experiments in which we evaluated the performance of the proposed organ localization approach using ensemble-learning techniques. We validated the effectiveness of the schemes in localizing five solid organs from the

DOI: 10.4018/978-1-4666-3994-2.ch068

torso CT scans. Finally, the article concludes with a discussion of the performance of the proposed scheme and future directions in this research.

The approach (Zhou, 2010) based on ensemble learning is introduced for the localization of major solid organs in three-dimensional (3D) CT scans. The objective of this approach is to design an automatic localization scheme for different solid organs, which is adaptive to both non-contrast and contrast-enhanced 3D CT images, and both normal and abnormal organs that appear differently on CT images. A typical ensemble learning method based on Haar-like features and the AdaBoost algorithm is used in this approach. A majority voting method is proposed to increase the robustness and accuracy; the following two constraints are imposed on this method:

1. The use of only a small number (about 100) of CT scans for training and
2. Rapid organ localization (within 1 min) using a standard computer.

BACKGROUND

3D images of anatomical structures of a patient are critical factors that support diagnosis, surgery, and therapy in clinical medicine. A modern radiographic CT scan can generate a 3D volumetric image that provides detailed anatomical information of a human torso within 10 s. However, a long time and experience are required to interpret such volumetric CT images by the traditional method to identify suspicious regions. Therefore, development of computer-based image analysis algorithms and visualization tools is expected to enable doctors increase efficiency and accuracy of interpretation, and reduce tedium and oversights during CT image interpretation.

A fundamental component of such a computer system is accurate and efficient organ segmentation. Separating a target organ region from the background by identifying the contour (surface in

3D) of the organ region is the major goal of organ segmentation. However, it may not be feasible to search for all voxels in a CT scan to determine the correct contour of a target organ. Organ localization by detecting the center position and deciding the range (a 3D bounding box) of the target organ in a CT scan is a practical pre-processing step that can be very useful for facilitating accurate organ segmentation. Such a 3D rectangle not only increases the accuracy and reduces the difficulty for further image segmentation, but also describes local geometry and density properties that can be used for diagnosis. In practice, a torso CT scan always shows the complex anatomical structures of all inner organs. Thus, automatic localization of different organ regions in torso CT scans is a very difficult problem that remains to be addressed.

Object localization is a major topic in the research field of computer vision, and ensemble learning such as AdaBoosting is an efficient way to solve face detection problems from pictures and videos (Viola, 2001; Lienhart, 2002). Recently, ensemble learning has also been used for 3D CT image analysis, including heart structure recognition (Zheng, 2008), liver segmentation (Ling, 2008), and anatomical landmark detection (Dikmen, 2008). Those studies have directly extended the Haar-like features (Viola, 2001) and probabilistic boosting-tree (Tu, 2005) that are used for face or nature object detection and applied them to 3D organ localizations on CT images. In another approach, decision forests based on long-range spatial context were successfully used for the localization of solid organs such as heart, lung, and liver in CT images (Criminisi, 2009). All of these works reported good performance and demonstrated the potential of using ensemble learning for organ segmentation and localization on CT images. However, such approaches inherited the drawback of classical ensemble learning that requires a large number of training samples so that the usefulness and robustness of the trained detector can be maintained for unseen samples. In particular, 3D CT images have a high feature

14 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:
www.igi-global.com/chapter/automatic-organ-localization-ray-images/77602

Related Content

A New Image Distortion Measure Based on Natural Scene Statistics Modeling

Abdelkader Ait Abdelouahad, Mohammed El Hassouni, Hocine Cherifiand Driss Aboutajdine (2012). *International Journal of Computer Vision and Image Processing* (pp. 1-15).
www.irma-international.org/article/new-image-distortion-measure-based/68001

Gesture Learning by Imitation Architecture for a Social Robot

J.P. Bandera, J.A. Rodríguez, L. Molina-Tancoand A. Bandera (2013). *Robotic Vision: Technologies for Machine Learning and Vision Applications* (pp. 211-230).
www.irma-international.org/chapter/gesture-learning-imitation-architecture-social/73193

Automated System for Crops Recognition and Classification

Alaa M. AlShahrani, Manal A. Al-Abadi, Areej S. Al-Malki, Amira S. Ashourand Nilanjan Dey (2017). *Applied Video Processing in Surveillance and Monitoring Systems* (pp. 54-69).
www.irma-international.org/chapter/automated-system-for-crops-recognition-and-classification/168900

Classification of Surface Electromyogram Signals Acquired from the Forearm of a Healthy Volunteer

Uvanesh K., Suraj Kumar Nayak, Biswajeet Champaty, Goutam Thakur, Biswajit Mohapatra, D. N. Tibarewalaand Kunal Pal (2016). *Classification and Clustering in Biomedical Signal Processing* (pp. 315-333).
www.irma-international.org/chapter/classification-of-surface-electromyogram-signals-acquired-from-the-forearm-of-a-healthy-volunteer/149396

SAR Image Recording Strategy to Improve Characteristics

Hocine Chebi (2021). *International Journal of Computer Vision and Image Processing* (pp. 58-65).
www.irma-international.org/article/sar-image-recording-strategy-to-improve-characteristics/275818