

ABSTRACT

DEEP learning with convolution neural networks (CNNs) has achieved state-of-the-art performance for automated medical image segmentation. However, automatic segmentation methods have not demonstrated sufficiently accurate and robust results for clinical use due to the inherent challenges of medical images, such as poor image quality, different imaging and segmentation protocols and variations among patients. Interactive segmentation often requires image specific learning to deal with large context variations among different images but current CNNs are not adaptive to different test images, as parameters of the model are learned from training images and then fixed in the testing stage without image specific adaptation. The Proposed system focus on interactive tumor segmentation of medical image sequences using deep neural network. The proposed work utilizes pattern based classification using neural network function. Adaptive Hierarchical motion segmentation is designed in the proposed area.

TABLE OF CONTENTS

CHAPTER NO	TITTLE	PAGE NO.
	ABSTRACT	v
	LIST OF FIGURES	viii
1	INTRODUCTION	1
	1.1 INTRODUCTION	1
	1.2 TYPES OF IMAGE SCAN	1
	1.3 INTRODUCTION TO IMAGE PROCESSING	3
2	LITERATURE SURVEY	4
3	METHODOLOGY	8
	3.1 EXISTING SYSTEM	8
	3.2 PROPOSED SYSTEM	8
	3.3 MODULE DESCRIPTION	8
	3.3.1 Pre processing	8
	3.3.2 Segmentation	9
	3.3.3 Back propagation	9
	3.4 SEGMENTATION	10
	3.5 ACTIVE COUNTERS	10
	3.5.1 Edge-based active counters	11
	3.5.2 Region-based active counters	12
	3.6 NEURAL NETWORKS	13
	3.6.1 historical background	13
	3.6.2 basics of neural networks	13
	3.6.3 neural networks versus conventional networks	15
	3.6.4 network layers	16
	3.7 DIAGRAMS	17
	3.7.1 System design	17
	3.7.2 Activity diagram	17
	3.7.3 Sequence diagram	19
	3.7.4 Use case diagram	20
	3.7.5 ER diagram	22
4	RESULTS AND DISCUSSION	25
5	SUMMARY AND CONCLUSION	30

5.1 CONCLUSION	30
REFERENCES	31
APPENDIX	32
A.SOURCE CODE	32
B.PUBLICATION	37

LIST OF FIGURES

FIGURE NO.	FIGURE NAME	PAGE NO.
3.1	NEURAL NETWORK LAYERS	14
3.2	SYSTEM ARCHITECTURE	17
3.3	ACTIVITY DIAGRAM	18
3.4	SEQUENCE DIAGRAM	19
3.5	USE CASE DIAGRAM	21
3.6	ER DIAGRAM	24
4.1	INPUT IMAGE	26
4.2	SALT AND PEPPER IMAGE	26
4.3	GREY SCALE IMAGE	27
4.4	FILTER IMAGE	27
4.5	IMAGE WITH 150 ITERATIONS	28
4.6	SEGMENTED PORTION	28
4.7	NEURAL NETWORK TRAINING	29

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Liver cancer remains associated with a high mortality rate, in part related to initial diagnosis at an advanced stage of disease. Prospects can be significantly improved by earlier treatment beginning, and analysis of CT images is a main diagnostic tool for early detection of liver tumors. Manual inspection and segmentation is a labor and time intensive process yielding relatively imprecise results in many cases. Thus, there is significant interest in developing automated strategies to support the early detection of lesions. Due to complex backgrounds, significant variations in location, shape and intensity across different patients, both, the automated liver segmentation and the further detection of tumors, remain challenging tasks.

1.2 TYPES OF IMAGE SCAN

Due to its detoxification function the liver one of the essential organs in the human body.

Radiologists and oncologists analyze computed tomography (CT) or magnetic resonance images (MRI) to study livers anomalies in shape and texture. These anomalies are important biomarkers for initial disease diagnosis and progression in both primary and secondary hepatic tumor disease. Often primary tumors of the abdomen such as breast, colon and pancreas cancer spread metastases to the liver during the course of disease. Therefore, the liver and its lesions are routinely analyzed in primary tumor staging. The RECIST protocol, which states to measure the diameter of the largest target lesion, has become clinical reference standard in tumor staging of liver cancer. From a global perspective primary liver cancer is the second most common cause of cancer death and is the sixth most frequent cancer. Computed tomography (CT) is the most commonly used image modality by radiologists and oncologists for liver lesion evaluation and staging. Furthermore, segmenting malignant liver tissues is important for cancer diagnosis, treatment, planning, and tracking treatment response. In addition, liver and tumor segmentation is also a prerequisite or a key asset for many treatment options such as thermal percutaneous ablation, percutaneous ethanol injection, radiotherapy

surgical resection and arterial embolization. However diagnostic imagery is expensive, very time-consuming, and poorly reproducible and its segmentations show operator-dependent results.

Since tumor volume is a better predictor than diameter, according to the Response Evaluation Criteria in Solid Tumor (RECIST), automatic segmentation is the most desirable goal.

However, a fully-automated segmentation of liver and its lesion remains still an open problem because different acquisition protocols, differing contrast-agents, varying levels of contrast enhancements and dissimilar scanner resolutions lead to unpredictable intensity differences between liver and lesion tissue. Many different types of lesions and especially tumor sub-types can occur in affected livers. Thus, these different types of tumors with varying contrast levels (hyper-/hypo-intense tumors) form obstacles to overcome. Modern methods struggle with abnormalities in tissues (such as after surgical resection of metastasis) or the size, shape and varying number of lesions.

Liver cancer was the second most common cause of cancer-induced deaths in 2015 according to the World Health Organization. Hepatocellular carcinoma (HCC) is the most common type of primary liver cancer which is the sixth most prevalent cancer. In addition, the liver is also a common site for secondary tumors. Liver therapy planning procedures would profit from an accurate and fast lesion segmentation that allows for subsequent determination of volume- and texture-based information. Moreover, having a standardized and automatic segmentation method would facilitate more reliable therapy response classification.

Liver tumors show a high variability in their shape, appearance and localization. They can be either hypodense (appearing darker than the surrounding healthy liver parenchyma) or hyperdense and can additionally have a rim due to the contrast agent accumulation, calcification or necrosis. The individual appearance depends on lesion type, state, imaging (equipment, settings, contrast method and timing), and can vary substantially from patient to patient. This high variability makes liver lesion segmentation a challenging task in practice.

1.3 INTRODUCTION TO IMAGE PROCESSING

Image Processing is a method to enhance raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life for various applications. Various techniques have been developed in Image Processing during the last four to five decades. Most of the techniques are developed for enhancing images obtained from unmanned spacecrafts, space probes and military reconnaissance flights. Image Processing systems are becoming popular due to easy availability of powerful personnel computers, large size memory devices, graphics software's etc. Image processing is a physical process used to convert an image signal into a physical image. The image signal can be either digital or analog. The actual output itself can be an actual physical image or the characteristics of an image.

Image processing is photography. In this process, an image is captured or scans using a camera to create a digital or analog image. In order to produce a physical picture, the image is processed using the appropriate technology based on the input source type. In digital photography, the image is stored as a computer file. This file is translated using photographic software to generate an actual image. The colors, shading, and nuances are all captured at the time the photograph is taken the software translates this information into an image. When creating images using analog photography, the image is burned into a film using a chemical reaction triggered by controlled exposure to light. The image is processed in a darkroom, using special chemicals to create the actual image.

CHAPTER 2

LITERATURE SURVEY

[1] Title: FRACTALNET: ULTRA-DEEP NEURAL NETWORKS WITHOUT RESIDUALS

Author Name: Gustav Larsson, Michael Maire

Year Of Publication: 2017

We introduce a design strategy for neural network macro-architecture based on self similarity. Repeated application of a simple expansion rule generates deep networks whose structural layouts are precisely truncated fractals. These networks contain interacting sub paths of different lengths, but do not include any pass-through or residual connections; every internal signal is transformed by a filter and nonlinearity before being seen by subsequent layers. In experiments, fractal networks match the excellent performance of standard residual networks on both CIFAR and Image Net classification tasks, thereby demonstrating that residual representations may not be fundamental to the success of extremely deep convolution neural networks. Rather, the key may be the ability to transition, during training, from effectively shallow to deep. We note similarities with student-teacher behavior and develop drop-path, a natural extension of dropout, to regularize co-adaptation of sub paths in fractal architectures. Such regularization allows extraction of high performance fixed-depth sub networks. Additionally, fractal networks exhibit an anytime property: shallow sub networks provide a quick answer, while deeper sub networks, with higher latency, provide a more accurate answer.

[2] Title: The Liver Tumor Segmentation Benchmark (LiTS)

Author Name: Patrick Bilic^{1a}, Patrick Ferdinand Christ¹

Year Of Publication: 2019

In this work, we report the set-up and results of the Liver Tumor Segmentation Benchmark (LiTS) organized in conjunction with the IEEE International Symposium on Biomedical Imaging (ISBI) 2017 and International Conference On Medical Image Computing & Computer Assisted Intervention (MICCAI) 2017. Twenty-four valid state-of-the-art liver and liver tumor

segmentation algorithms were applied to a set of 131 computed tomography (CT) volumes with different types of tumor contrast levels (hyper-/hypo-intense), abnormalities in tissues (metastases) size and varying amount of lesions. The submitted algorithms have been tested on 70 undisclosed volumes. The dataset is created in collaboration with seven hospitals and research institutions and manually blind reviewed by independent three radiologists. We found that not a single algorithm performed best for liver and tumors. The best liver segmentation algorithm achieved a Dice score of 0.96(MICCAI) whereas for tumor segmentation the best algorithm evaluated at 0.67(ISBI) and 0.70(MICCAI). The LiTS image data and manual annotations continue to be publicly available through an online evaluation system as an ongoing benchmarking resource.

[3] Title: Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks

Author Name: Shaoqing Ren_ Kaiming He Ross Girshick Jian Sun

Year Of Publication: 2016

State-of-the-art object detection networks depend on region proposal algorithms to hypothesize object locations. Advances like SPPnet [7] and Fast R-CNN [5] have reduced the running time of these detection networks, exposing region proposal computation as a bottleneck. In this work, we introduce a Region Proposal Network (RPN) that shares full-image convolution features with the detection network, thus enabling nearly cost-free region proposals. An RPN is a Fully-convolution network that simultaneously predicts object bounds and objectness scores at each position. RPNs are trained end-to-end to generate high quality region proposals, which are used by Fast R-CNN for detection. With a simple alternating optimization, RPN and Fast R-CNN can be trained to share convolution features. For the very deep VGG-16 model [19], our detection system has a frame rate of 5fps (including all steps) on a GPU, while achieving state-of-the-art object detection accuracy on PASCAL VOC 2007 (73.2% mAP) and 2012 (70.4% mAP) using 300 proposals per image

[4] Title: Detection-aided liver lesion segmentation using deep learning

Author Name: Anonymous

Year Of Publication: 2017

A fully automatic technique for segmenting the liver and localizing its unhealthy 2 tissues is a convenient tool in order to diagnose hepatic diseases and assess the 3 response to the according treatments. In this work we propose a method to segment 4 the liver and its lesions from Computed Tomography (CT) scans using Convolution Neural Networks (CNNs) that have proven good results in a variety of 6 computer vision tasks, including medical imaging. The network that segments the 7 lesions consists of a cascaded architecture, which first focuses on the region of 8 the liver in order to segment the lesions on it. Moreover, we train a detector to 9 localize the lesions, and mask the results of the segmentation network with the 10 positive detections. The segmentation architecture is based on DRIU [8], a Fully 11 Convolution Network (FCN) with side outputs that work on feature maps of 12 different resolutions, to finally benefit from the multi-scale information learned by 13 different stages of the network. The main contribution of this work is the use of 14 a detector to localize the lesions, which we show to be beneficial to remove false 15 positives triggered by the segmentation network.

[5] Title: Automatic Liver and Lesion Segmentation in CT Using Cascaded Fully Convolution Neural Networks and 3D Conditional Random Fields

Author Name: Patrick Ferdinand Christ¹, Mohamed Ezzeldin A

Year Of Publication: 2017

Automatic segmentation of the liver and its lesion is an important step towards deriving quantitative biomarkers for accurate clinical diagnosis and computer-aided decision support systems.

This paper presents a method to automatically segment liver and lesions in CT abdomen images using cascaded fully convolution neural networks (CFCNs) and dense 3D conditional random fields (CRFs). We train and cascade two FCNs for a combined segmentation of the liver and its lesions. In the first step, we train a FCN to segment the liver as ROI input for a second FCN. The second FCN solely segments lesions from the predicted liver ROIs of step 1. The segmentations of the CFCN using a dense 3D CRF that accounts for both spatial coherence and appearance. CFCN models were trained in a 2-fold cross-validation on the