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Multiorgan Detection: Deep Learning Based Techniques and Research Directions

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Abstract: ***Automatic organ segmentation plays an important role in clinical procedures such as planning of radiation therapies and in computer-aided diagnostic systems. Several state-of –art techniques are available for multiorgan segmentation, however deep learning methods are doing exceptionally well and become the methodology of choice to analyze medical images. This intensively carried out work is conducted for deep learning methods applied on various organs in abdominal CT images. Firstly, this paper formulates segmentation, semantic segmentation problem and their methods. Secondly, multiorgan detection techniques based on deep learning along with their contributions, chosen datasets and gaps are discussed. It presents the metrics used to evaluate these methods. Finally, interesting conclusions has been drawn which will add to do future work using deep learning.***

Keywords: ***Deep Learning, Semantic Segmentation, Fully Convolutional Neural Network etc.***

I. INTRODUCTION

Computer vision is an active field of research that deals with the deep understanding of image content. It includes various sub-domains such as object detection, recognition, image understanding, classification, segmentation etc [1]. With the advancement in technologies like CT, MRI etc., images are considered as important part of clinical applications. Thus biomedical image analysis is the crucial application of computer vision. But it is high level task to gain understanding of medical images of different modalities. Medical imaging modalities have provided powerful insights to examination and understanding the structural and functional architecture of human anatomy and are widely used for intervention, diagnosis and management of clinical disorders. With the emergence of new technology and procedures to acquire, it becomes immense necessity to explore ever more subtle anatomical correlations in CT, MRI and other anatomies.

Multiorgan Detection (MOD) is a process of segmenting and detecting various organs from abdominal CT scans.

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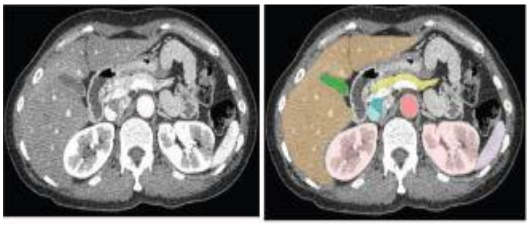
Abdominal is the crucial and complex body part clinically. Various abdominal organs include kidney, spleen, liver, pancreas, stomach, esophagus, gallbladder, aorta, inferior vena cava etc. Manual detection of organs in CT images may be the direct approach.

But it is impractical solution to have radiologists for manual individual organ detection and it consumes more resources such as time, material and labor. That's why lots of work has been conducted to automate organ segmentation systems [2]. Although huge amount of research is carried out for single organ segmentation [3]–[8] but more attention is yet to be required for multiorgan segmentation. Figure 1.a and Figure 1.c shows the abdominal CT scan image and Figure 2 is the 3D rendering of abdominal image.



(a) (b)

Fig. 1.(a) Input Abdominal CT scan image and (b) Output Segmented image to detect multiple organs [9],[10]

Segmentation of organs at risk (OAR) is helpful in planning therapies [12]. Multiorgan segmentation plays important role in computer aided diagnostic systems (CAD) [12]. In general term, surgery planning models and delivery systems are supported by segmentation based patient-specific models. It is helpful in inserting endoscopy in endoscopic procedure [12]. In many clinical procedures such as detection of metastasis [13]-[14] and radiotherapy [2] requires analysis of different anatomies.

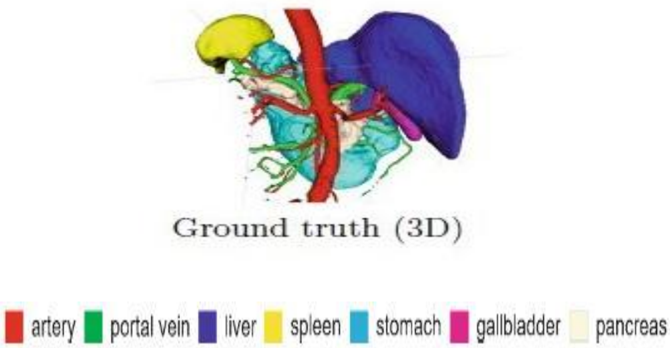


Fig. 2.3D surface rendering of Abdominal Image [11]

Multiorgan segmentation is needed to do same. The mapping of multiorgan segmentation to a series of single-organ segmentations is affected by number of errors while transitioning through various stages. However, these errors are removed by a difficult technique of post-segmentation correction [11]. As there is no problem related to segmentation sequence or propagation of errors in multiorgan methods, we concentrate on these methods [15].

II. BACKGROUND CONCEPTS

A. Segmentation:

Segmentation is the process of assigning every pixel to some region based on its color, intensity, texture etc. Homogeneous regions will be clustered together automatically [16], [17]. Generally, there are various segmentation methods which are given as follows:

Thresholding Method:

It can be defined as the process of dividing image into two parts black (0) and white (1) based on threshold value. Pixel will be considered into black if pixel value is less than threshold value and vice-versa. In other words, binary image will be created [18].

Clustering:

It is the unsupervised learning method which forms clusters based on some kind of homogeneity [19]. There are various clustering methods such as hard clustering, K-means technique, Fuzzy clustering etc.

Region Growing Technique:

In this technique, seed locations are selected initially and starting from these seed locations, sub-regions are formed based on the similarity properties of neighboring pixels. But in each of the above mentioned method there is no understanding that pixel belongs to which class. Hence, segmentation divides the mage into various segments without labeling any pixel. Figure 3 and 4 shows examples of image segmentation.

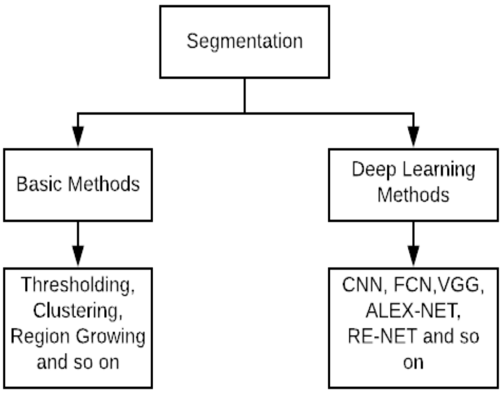
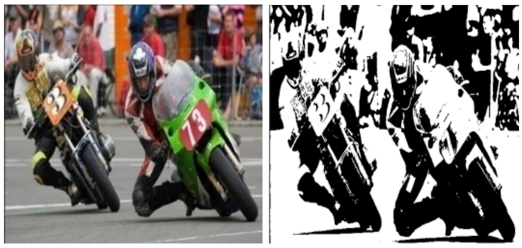


Fig. 3.Basic Techniques for Multi organ Detection

B. Semantic Segmentation:

Semantic segmentation will categorize each pixel into predetermined class. It answers what and where both. Therefore, image is partitioned into different meaningful parts. In Figure 5, there are 7 predetermined classes. Each pixel is semantically categorized into these classes. Object detection, image segmentation and semantic segmentation tasks are interdependent. For example, label of pixels are benefitted by image segmentation and object detection. Similarly, object detection may depend upon segmentation of images



(a) (b)

Fig. 4.(a) Original RGB Image (b) Segmentation using Reinforced Fast Marching method in MATLAB 2015

(a) (b)

Fig. 5.Original Image (b) Semantic Segmentation [28].

In other words, semantic segmentation problems contain the difficulties of both segmentation and object detection. Major challenge for semantic segmentation is over-segmentation problem [20]. There are various semantic segmentation methods available in literature such as conditional random field (CRF), Ontology based semantic segmentation, convolution neural network CNN [21], [22], fully convolutional network (FCN) [23], Alesxnet [24], [25], VGG [26], [27], recurrent network (Re-NET) etc. Figure 6 shows the example of semantic segmentation.

III. DEEP LEARNING BASED MULTI ORGAN TECHNIQUES

Trend of exploring and analyzing CT images is increasing over the years. Many algorithms have been developed and reported in literature to segment multiple-organs in abdominal CT images. Comprehensive literature survey of the newly emerging techniques in multiorgan segmentation is given below.

A. Multiorgan Segmentation Based on Deep Learning:

Eli Gibson et al. [12] presented a deep learning based technique useful in biliary procedures and for navigation in endoscopy using dense V-networks FCN. It can be applied to organs related to GI tract, surrounding organs such as liver, pancreas and spleen. Though this method outperforms for all organs except duodenum but clinically acceptable accuracies are not reached yet. **Holger R.Roth et al.** [29] proposed a two stage technique for multiorgan segmentation.

In the first stage, 3D FCN is used in order to extract the candidate region. FCN is trained on 3D CT scans and focus of this stage is to roughly extract organs region. Thus model does not properly segment organs around their boundaries particularly small organs.

This problem is removed in the second stage. Second stage removes inaccuracies around boundaries of small organs in cascaded fashion. The output of first stage acts as input to second stage. Though this technique is tested on unseen different datasets but different anatomical structures should be added to ensure the method's generalizability and robustness. Better results can be achieved by combining different models. **Yangzi Yang et al**. [2] built new architecture namely FCN-DecNet. It is based on FCN model and more layers are added to it such as de-convolutional layer, fusion layer and new unpooling layer. Rough segmentation is done using multi-scale weight probabilistic atlases. Further, segmentation is optimized by integrating the results of FCN-DecNet and multi-scale weight probabilistic atlases. This method performed well for large organs. However, technique is not tested for small organs and it is semi-automated. Also, larger database should be used to train the model for better results. **Hideki Kakeya et al.** [9] devised a model which combines the power of U-Net and probabilistic atlases (PA's). PA's are used to give rough estimation about organs locations and U-Net provides the volumetric segmentation. This technique is efficient in terms of dice score but they have used very limited data. Larger dataset should be used to enhance the reliability of the technique. **Holger R. Roth et al.** [11] presented an auto-context multi-scale pyramid approach based on 3D FCN which is tested on multiple larger datasets to improve its generalizability. This method does not need any additional FCN for different scales and different contexts. Information from different image scales and contexts is combined by auto context principle. It works well both at higher and lower resolutions. This study did not consider duodenum along with other organs.

Most of the deep learning methods rebuilt the network architecture for multi organ segmentation by changing the network from plain to cascaded, pyramid, residual etc. **Yan Wang et al.** [15] proposed a method which is based on the idea that instead of making complex network architecture, change the pathway to select samples for training. Sample selection criterion is different for hard and easy samples. Hard samples are those samples which involves small organs and more details. They are difficult to segment and may cause errors. Relaxed Upper Bound Confident (RUCB) is used to select hard samples. This makes the training process efficient and fast. Desired accuracies are not achieved for small organs. They did not consider computational time to prove their technique faster. **Yuyin Zhou et al.** [30] presented a semi-supervised technique based on deep network. There are two models in this approach: one is student model and other one is teacher model. Firstly, teacher model is labeled manually by radiologists and verified from experts. The trained model and the information from different planes such as sagittal, coronal and axial planes is fused which is helpful in assigning pseudo-labels to unlabeled data. Student model is trained on manual labeled data and automatically labeled data. It fused the estimations from three different planes that's why named as multi-planar deep network model. This technique performed well but average computation time is 4.5 minute which is not acceptable in practical applications. **Mans Larsson et al.** [31] provides the fully automatic approach which works in two stages. In the first stage, multi-atlas based method is used for initial estimation of seeds. In the second stage, CNN is applied for organ segmentation which ensures to detect local as well as global context. There is significant difference in validation data and test data results. Thus this method does not give generalizability. **Peijun Hu et al.** [32] presented a technique which provides the training to 3D CNN model and generates probability feature map. Based on this feature map segmentation is performed. These results are further improved by multi phased level set. They have tested only on large organs.

Table I Main Papers of Multiorgan Detection Algorithms based on Deep Learning

	Dataset	**Metrics**	**Research Gaps**
Dense V-Networks [12]	47 CT images from Beyond the Cranial Vault' (BTCV) dataset and 43 subjects from unseen dataset.	Dice, symmetric mean, Hausdorff distance and boundary distance	Though this method outperforms for all organs except duodenum but clinically acceptable accuracies are not reached yet. Spleen 0.95, L.Kid. 0.93, Gallbladder 0.73, Esophagus 0.71, Liver 0.95, Stomach 0.87, Pancreas. 0.75, Duodenum 0.63
3D FCN [29]	-121 clinical CT images acquired at different hospitals that include 150 CT scans. - TCIA Pancreas CT dataset (Rotzh) is used for comparison.	Dice similarity score and Computational time	Though this technique is tested on unseen different datasets but different anatomical structures should be added to ensure the method's generalizability and robustness. Better results can be achieved by combining different models.

DL Method	Dataset	Metrics	Research Gaps
FCN-DecNet [2]	12 patients CT volumes and each have about 70 abdominal slices.	Dice Index	This method performed well for large organs. However, technique is not tested on small organs and it is semi-automated. Also, larger database should be used to train the model for better results
FCN Voting Method Medical [14]	640 3D volumetric CT scans, 240 different CT scans	Intersection over union(IU)	Spleen .880, Liver .937Gallblader .632 Right Kidney .885Left Kidney 0.857 Inferior Vena Cava0.705 Pancreas 0.553
Multi Scale Pyramid of 3D FCN [11]	377 CT Images	Dice	This method does not need any additional FCN for different scales and different contexts. Information from different image scales and contexts is combined by auto context principle. It works well both at higher and lower resolutions. But this study did not consider duodenum along with other organs
Sample Selection by Relaxed Upper Con_dent Bound [15]	120 CT Scans	Dice	This approach makes the training process efficient and fast. Desired accuracies are not achieved for small organs. They did not consider computational time to prove the technique faster Duodenum-64.86 Gallbladder-79.68 Pancreas-78.48
DeepSeg [31]	30 CT images and VISCERAL challenge data is used for training.	Dice	This method is able to capture local as well as global context of CT image. But There is significant difference in validation data and test data results. Thus this method does not give generalizability

IV. EVALUATION METRICS

A. Dice Coefficient

Generally, dice coefficient is used to evaluate segmentation results. It is the measure of overlap or similarity between two sets say X and Y. So, it is calculated as overlap measure divided by size of individual objects or sets.

$$\text{Dice Coefficient} = \frac{2*(X\cap Y)}{|X|+|Y|} \quad (1)$$

B. Intersection over Union (IoU)

It is the measure of area of overlap and area of union. It is also known as Jaccard Index. From the following equation it is clear that it calculates the common pixels between two bounding boxes A and B divide it by total pixels present in A and B.

$$\text{IoU}=\frac{A\cap B}{A\cup B} \quad (2)$$

where A and B are target and prediction respectively.

C. Hausdorff Distance

It is mostly used for medical image segmentations. It gives the distance between two set of pixels. Select a pixel from image A and calculate distance from every other pixel in B. Repeat the process for each pixel in A. Maximum value among all the distances will calculates D (A, B). Ranking will be given to each point of A based on its distance in B.

$$D(A,B) = \max(D(A,B),D(B,A)) \quad (3)$$

where X and Y are algorithm and ground truth segmentations respectively.

V. CONCLUSION

Despite so much work on multiorgan detection techniques for abdominal CT images, still there are interesting research directions which can be explored in future.

A. Organ Selection

It is clear from the research gaps discussed in section III that significant results are achieved for large abdominal organs such as liver, kidney, spleen etc. however there is a huge room to work on small organs like pancreas, esophagus, duodenum etc. Quite a few studies reported multiorgan segmentation with duodenum organ which plays crucial role in video-endoscopy. Thus, satisfactory research work is required for clinical acceptance for small organs especially pancreas and duodenum [2].

B. Computational Runtime

With the advancements in deep learning techniques, the major challenge today is to maintain accuracy levels while reducing computational run time with increasing number of anatomies [12].

C. General Models

The multiorgan segmentation models are generated based on shape and location of organ which may vary from patient to patient. Thus segmentation results got affected by generality of these models on target specific images. A clinically accepted robust model is the need of hour which will add to future work.

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