# Patient Oriented Neural Networks to Overcome Challenges of Abdominal Organ Segmentation in CT Angiography Studies

M. Alper Selver[1], Aykut Kocaoğlu[2], Hasan Akyar[1], Oğuz Dicle[3], Cüneyt Güzeliş[1]

[1]Electrical and Electronics Engineering Department, Dokuz Eylül University, Izmir, Turkey.
alper.selver@deu.edu.tr, hasan-akyar@hotmail.com, cuneyt.guzelis@deu.edu.tr
[2]Izmir Vocational School, Dokuz Eylül University, Izmir, Turkey.
aykut.kocaoglu@deu.edu.tr
[3]Department of Radiology, School of Medicine, Dokuz Eylül University, Izmir, Turkey.
oguz.dicle@deu.edu.tr

## Abstract

**Segmentation of organs from abdominal Computed Tomography Angiography (CTA) images is one of the essential steps in quantitative measurements (e.g. volume, size etc.). Due to gray level similarity of adjacent organs, injection of contrast media, high variations in organ borders, partial volume effects and atypical shapes, effective segmentation of these organs is a very difficult task. In this paper, we propose a semi automatic and neural network based segmentation method that adapts its parameters according to each dataset by learning the data characteristics in parallel to segmentation process, thus named patient oriented neural networks. Proposed approach makes the design of the overall system fully automatic (if the initial segmentation result is also automatic) without requiring any training set. The segmentation results are evaluated by using area error rate and they show that, the proposed algorithm gives promising results in most of the challenging aspects of abdominal organ segmentation.**

## 1. Introduction

Measurements (i.e. volume, size etc.) of the abdominal organs (i.e. liver, spleen, right and left kidneys) are important in the evaluation procedures prior to diagnosis, therapy and surgery. One of the routine techniques for evaluation of patients is CT-Angiography (CTA) [1], which is a widely used radiographic technique for the rendering of abdominal organs. Instead of conventional angiography, CTA provides minimally invasive intervention, diminished patient morbidity, cost, and radiation exposure to patients and staff. Before 3D rendering and the measurement of necessary parameters from CTA, accurate segmentation of the organs from surrounding tissues and other organs is necessary. Since the number of image slices is usually high, manual segmentation of these organs on each slice is time consuming and tedious. Also the results highly depend on the skill of the operator. Therefore, (semi) automatic segmentation procedures are needed while there are several challenging issues in (semi) automatic segmentation [2].

First of all, the gray level values of adjacent organs in the abdomen are similar to each other (Fig. 1.a-1.b) which limit the performance of thresholding and morphology based techniques [3-6]. Moreover, the organs and tissues can get very different values than expected Hounsfield range for different patient datasets or in different slices of the same dataset due to the injection of contrast media (Fig. 1.c). Moreover, the parenchymas of these organs become inhomogeneous due to the enhanced vessels. These prevent the usage of the techniques that only use gray level and gradient [7-12]. Finally, the anatomical structure of these organs in different image slices is different (Fig. 1.e, 1.f) and their shape and position can vary significantly in different patients and different CTA series (Fig. 1). Patients might also have atypical (i.e. unusual size or orientation) organs (Fig. 1.d) that limits the use of shape based techniques.

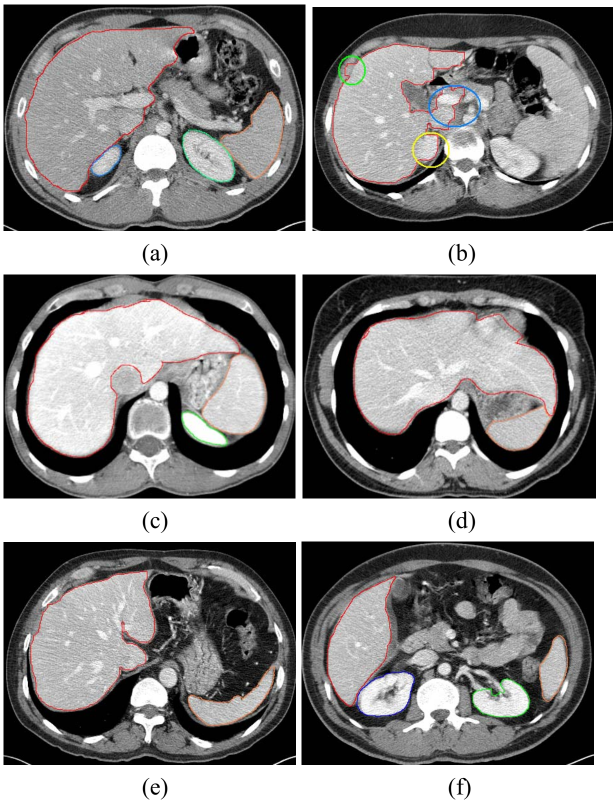



**Fig. 1.** Examples of CTA images and representation of challenging difficulties in segmentation a) Four organs of interest, liver: red, right kidney: blue, left kidney: green, spleen: orange, b) challenges in segmentation (See text for details), c) effect of contrast agent, d) atypical liver, e) a slice from the beginning and, f) a slice from the end of a CTA series.

In abdominal image segmentation, Artificial Neural Networks (ANN) is used for gray level classification in [11] and for feature based recognition in [12]. The technique proposed in [11] require several manually segmented image as training data while in [12] training is done with a limited set of images. A contextual NN is proposed in [13], but the results show that it fails where the gray level of the desired region is too close to the adjacent tissues. In [14], texture of the abdominal organs is used for segmentation. In a more recent, neural networks are used in a way that the algorithm updates the weight of the ANN in parallel based segmentation process to adapt the changes in the dataset for liver segmentation from CTA studies [15].

Our strategy for overcoming these difficulties involves a ANN based strategy which is not trained in advance. Instead, it is capable of adjusting its parameters by an iterative training and weight update mechanism. The main reason for this approach is that the ranges of the parameter values differ significantly from patient to patient, and these wide ranges decrease the efficiency of the method when an ANN is trained even with a diverse training set. Thus, the wide range of parameters between different slices/datasets can be adjusted properly. In other words, we propose a method which examines and adapts its parameters according to each patient, so named patient-oriented neural network.

The rest of the paper is organized as follows. The properties of the patient datasets are presented in Section 2. The segmentation system is explained in Section 3. The evaluation of the system is given in Section 4. Finally, future plans for the improvement of the system are discussed in Section 5.

## 2. Patient Datasets

Our datasets were acquired after contrast agent injection at portal phase using a Philips Secura CT with 2 detectors and a Philips Mx8000 CTA with 16 detectors, both equipped with the spiral CTA option and located in Dokuz Eylül University Radiology Department. This technique scans the entire abdomen in 15 to 30 seconds and offers several advantages. Its speed also reduces or eliminates respiratory mis-registration between slices. 20 datasets (CTA series), which were obtained by these scanners, consist of 12 bit DICOM images with a resolution of 512 x 512. The datasets were chosen randomly from the Picture Archiving and Communication System (PACS). All of the 20 CTA series have 3 to 3.2mm slice thickness and this corresponds to a slice number around 90 (minimum 77, maximum 105 slices).

## 3. Methodology

In this paper, a four step algorithm (Figure 2) for segmentation of abdominal organs from CTA images is being proposed. The algorithm is an extended version of the liver segmentation algorithm which is introduced in [16] and designed particularly for the segmentation of the liver from CTA series. In this modified and extended version, the algorithm is capable of segmenting all abdominal organs including liver, spleen, right kidney and left kidney. The price that is paid to extend the algorithm from segmenting only liver to all abdominal organs is switching from automatic to semi-automatic. However, being semi-automatic, the proposed algorithm only requires only one manually segmented slice for each organ. In comparison to the number of slices in the complete series (usually around 100), we can say that the user interaction and the dependency to user expertise level are minimized.

The algorithm starts with a manually segmented slice in which the organ of interest (i.e. liver, kidney, spleen or right/left kidneys) is manually segmented and left alone by a physician. These manually segmented slices will also be called as initial image(s) in the rest of this paper. Starting from a manually segmented slice, the algorithm runs through the end of the data set and then again starting from the same manually segmented slice it runs through the beginning of the data set to complete the segmentation process. This process is done for each organ to segment.

Before starting to explain the segmentation algorithm in detail, it might be useful to point possible pre-processing operations which can have a significant affect on the performance. For reducing the computation complexity and for increasing the performance of the segmentation algorithm, as much irrelevant information as possible should be removed from the images at a preprocessing stage. From the anatomy knowledge, we know that the abdominal organs are surrounded by the ribs, spine, fat tissue, and muscle tissue. These tissues are out of interest in abdominal organ segmentation and removing them might probably result in better segmentation and/or classification performance. Also the unnecessary parts of the image starting from the top (from the first non-zero pixel) can be removed. These preprocessing steps can be done for the complete series of CTA images in advance (to the whole dataset at once prior to segmentation process) or can also be done iteratively (slice by slice, during or before the segmentation process). Of course, one very important point is not to remove any information that belong to the organs of interest when removing the others. In this paper, we will no further go into details about possible preprocessing steps due to the lack of space and will focus on the methodology of segmentation.

The four main steps of the algorithm (Figure 2) can be explained as follows:

**Step 1)** The main aim of this step is the initial training of the neural network, Multi Layer Perceptron (MLP) [17]. For this initial training, manually segmented slice (initial image) is used. Let us call the original form of this slice as ***"INitial Image"*** **(INI)** and manually segmented version of it as ***"segmented initial image"*** **(SINI)**. SINI is a binary image where 1 represents the pixels that belong to the manually segmented organ and 0 values represent the rest. From the INI, two statistical features are extracted. These are the mean, which is being used to represent the homogeneous inner side (i.e. parenchyma) of the organs and the standard deviation, which is used to enhance the borders of the organs. The third feature, the distance transform is then extracted from SINI. Here, the distance transform feature is used to represent the direction, alignment and the position of the organ (Fig. 3). This information is provided by a metric, which is calculated to measure the total Euclidean distance along the horizontal, vertical, and diagonal directions, defining the separation of the pixels in an image (Besides its use in this step, this feature will be used to get adjacent slice information in step 2).

The network is trained initially by using the calculated three features as the training data and the SINI as the desired output. At the network output, each input pixel is classified as belonging to the liver region or lying outside the liver region on the basis of these features. After this initial training, weights are updated, the network had been initialized and the iterative segmentation process starts (Step 2, Step 3 and Step 4).

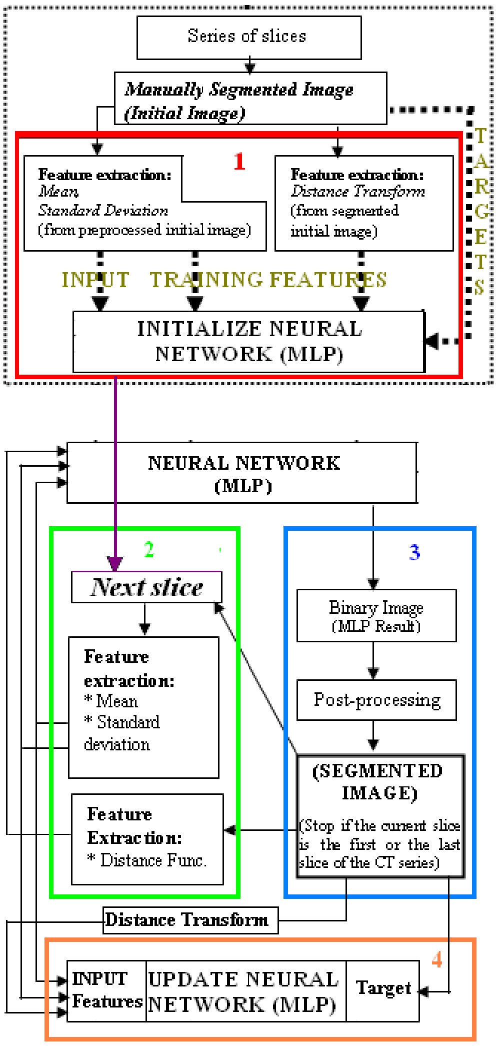



**Fig. 2.** Segmentation process by using MLP, (1) Preprocessing of all images is followed by the selection and segmentation of the initial image. The initial training is done by using the segmented initial image as the desired output and the feature vectors obtained from initial and segmented initial images as training data, (2) then, the algorithm proceeds to next slice and at each slice previously found weights are used for classification with MLP. (3) Post-processing is applied to obtain the segmented image, (4) the weights are updated using the current segmented image as the desired output and the feature vectors obtained from the current slice as training data

**Step 2)** After the initial training of MLP using INI and SINI and post processing of the MLP result, iteration proceeds to the next slice (preceding or succeeding based on the direction of the iteration). Let us call this slice Current Image to Segment (CIS).

Mean and standard deviation features are calculated for the CIS. However, this time, the distance transform is calculated from the previously segmented image (segmentation result of the previous slice). By using these features and the previously adjusted weights (weights adjusted for the previous slice), the CIS is classified using MLP.

**Step 3)** The result obtained from the neural network usually need a few more basic image processing operations for refinement. These may include filtering (i.e. median, Gaussian etc.) for boundary smoothing, morphological operations (i.e. erosion, dilation, reconstruction etc.) for removing mis-segmented parts or enhancing/suppressing information. The post-processing steps for each organ of interest is usually different and requires different operations or at least different parameters related to its size, shape, connectedness (i.e. liver may have dissect into two regions) and adjacent tissues and/or organs. These post-processing steps will not be discussed here but [16] explains the details of the post-processing steps for liver segmentation. After the post-processing, the remaining binary mask is applied to original image and the segmentation result is obtained. Then, the algorithm switches to step 4.

**Step 4)** After the segmentation of the CIS, the network is trained again and the weights are updated by using the features (calculated for the original CIS (i.e. mean and standard deviation) and segmented CIS (i.e. distance transform) as the input and the new segmented CIS as the desired output. The training time is reduced significantly by using the previously found weights as the initial weights of the update process.

In our algorithm, the distance transform gives information about the organ location at the adjacent (preceding/succeeding) slice. Since the sizes and locations of the abdominal organs do not change dramatically between adjacent slices, the distance transform of a segmented organ (Figure 3) gives quite important information about it location and orientation at the adjacent (preceding/succeeding) slice. (This way of segmentation is actually the automatic version of the method that the physicians use for manual segmentation studies. When the physicians are not sure about exact boundary of an organ in a slice, they check adjacent slices and try to determine border based on them.)

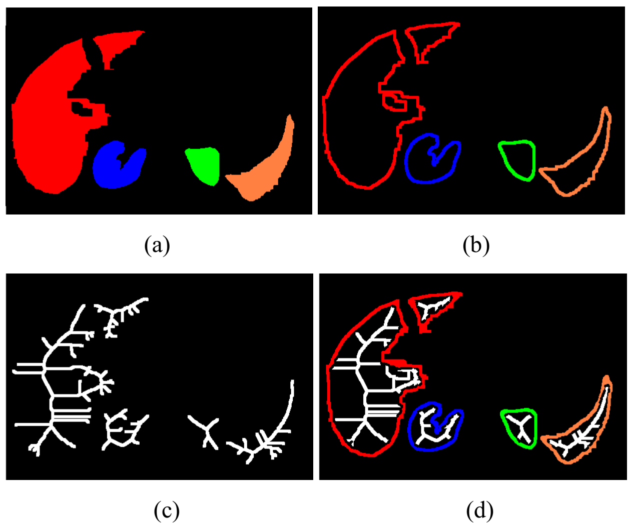



**Fig. 3.** a) Four manually segmented organs: Liver: Red, Right Kidney: Blue, Left Kidney: Green, Spleen: Orange; b) borders of these organs c) Result of the distance transform (skeletonization) d) Merging organ borders with skeletonization to show the effectiveness of the distance transform in the representation of abdominal organs. (*Dilation operation is applied to figures b, c and d for better visual representation. Actually, each line has only one pixel thickness.*)

Finally, the algorithm switches back to Step 2, in other words, proceeds to the next (succeeding/preceding) slice if all the images are not segmented or a stopping criteria (i.e. number of the pixels that belong to the segmented object is smaller than a predefined value) is not reached. These four steps should be repeated for each organ of interest since the method is capable of segmenting only one at once.

## 4. Simulations and Results

20 CTA series have been used in the evaluation of the proposed method. All of these CTA series contain images between 77 and 105 slices all of which are in DICOM format and have 3 to 3.2mm slice thickness.

The features (i.e. mean, standard deviation and distance transform) are calculated for overlapping kernels of size 9x9. The size of the kernel is decided after extensive experimentation and by following the proposed sizes in literature [11, 12].

The MLP structure used for the segmentation consists of 3 neurons at the input layer, 8 neurons at the hidden layer with a bias input between +/- 1. The biases are updated along with weights during error backpropagation [16]. The output layer consists of l neuron. The output of the network lies between 0 and 1 for each pixel and it is thresholded by 0.5. Then, for an input region belonging to the organ of interest, the output becomes 1 for the organ of interest and 0 for the rest.

The segmentation results are evaluated by using the area error rate (AER) [11], or in other words, by using Tanimoto coefficients. If we name the region segmented by the algorithm as Automatic Segmentation Result (ASR) and the region segmented manually as Manual Segmentation Result (MSR), then Defining a Region Of Union Region ROU as ASR $\bigcup$ MSR and a Region Of Intersection (ROI) as ASR $\bigcap$ MSR, AER is equal to:

$$AER = \frac{ROF - ROI}{MSR} \times 100\%$$

In our evaluation, AER is calculated directly (without any boundary modification) between the manually and automatically segmented images.

Figure 4 shows the shows the average AER for each patient data set (on a logarithmic scale) and Table 1 shows the statistic of the results.

**Table 1.** AER percentages of the segmented abdominal organs of interest using proposed methodology

| AER (%) | Mean AER | Max. AER | Min. AER | Standard Deviation |
|---|---|---|---|---|
| **Liver** | 15.28 | 20.07 | 12.51 | 2.19 |
| **Spleen** | 12.21 | 13.85 | 9.48 | 1.64 |
| **Right Kidney** | 9.02 | 10.84 | 7.48 | 0.96 |
| **Left Kidney** | 7.97 | 9.80 | 6.12 | 1.34 |

The results show that the AER ranges for the organs of interest are segmented with fair performance. It should be noted that AER is a very sensitive error measure which is affected significantly even with a single pixel difference between ASR and MSR images. Concerning this fact, we can conclude that the right kidney and left kidney are segmented with high performance. This is mainly because of their relatively simpler shape. On the other hand, liver and spleen has more AER due to their complex size shape and orientation.

The results also show that the proposed method has shown promising performance at handling several difficulties. The method is especially useful when dealing with atypical size, shape and orientation. This is because of the adjacent slice information provided by the distance transform of the previously segmented slice. Pre-processing and post-processing steps are important in the improvement of the methodology. Although there is no application where the algorithm completely fails, it is possible that it might fail if the organ of interest is wrongly segmented in a slice.

The slice thickness is also an important factor. Slice thickness up to 3.2 mm will be fine and smaller values will increase the accuracy. On the other hand, values higher than 3.2. mm might cause problems to the limited adjacent slice information provided.

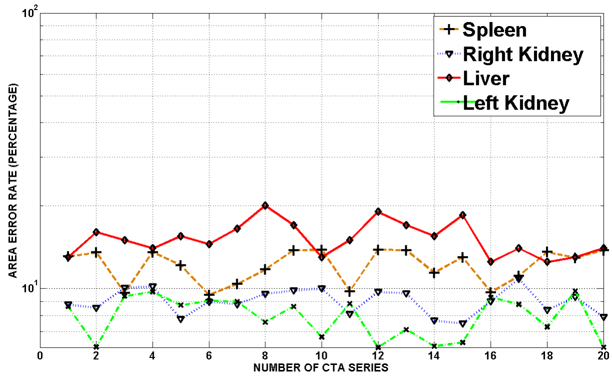
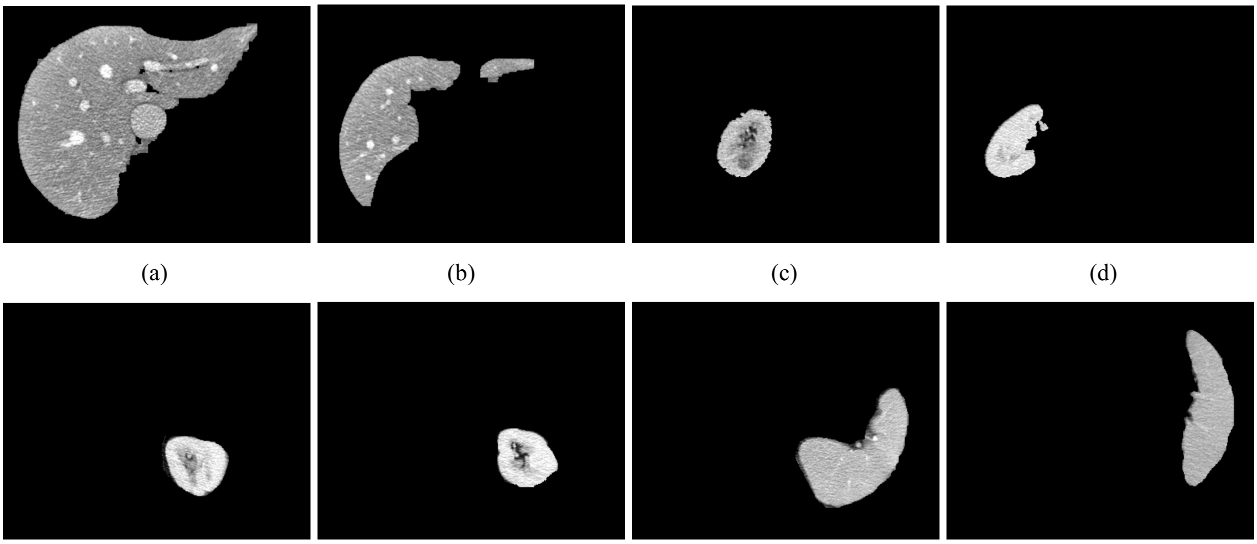



**Fig. 4.** The AER values for each organ of interest at each of 20 CTA datasets (plot is on logarithmic scale for better representation of differences and deviations

## 5. Conclusions

A robust and efficient method that can automatically segment the abdominal organs in any CTA series is introduced. The success rate is calculated as 85.86% for liver, 91.13% for right kidney, 92.33% for left kidney and 87.47% for the spleen. The robustness of the method follows from its capability of handling the challenges of abdominal organ segmentation by using a new training and classification strategy, namely patient oriented neural networks. This network learns the characteristics of a patient dataset for each slice in parallel to the segmentation process and adapts its parameters according to these characteristics. Our iterative segmentation algorithm uses classification of pixels (using a Neural Network i.e. Multi Layer Perceptron - MLP) together with adjacent slice information. The developed method gives promising performance for different modalities, varying contrast, dissected regions and atypical shapes.

Results indicate that we have effectively overcome the challenging difficulties explained before. This performance is achieved with introducing the distance transform as a feature for each slice and then using this information in the succeeding slice to reveal three dimensional properties of the organs which can not be obtained by the set of slices processed individually or sometimes all together as a 3D data.



(a) (b) (c) (d)

(e) (f) (g) (h)

**Fig. 5.** Some examples of segmentation results, representing the wide variety in the same, Hounsfield range, size, position and orientation of the abdominal organs in CTA series a), b) liver, c), d) right kidney, e), f) left kidney, g), h) spleen.

The classifier update at each step improves the robustness of the system which provides the possibility of high performance also for the CTA series coming from different modalities.

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