An Efficient Pipeline for Abdomen Segmentation in CT Images

Hasan Koyuncu¹ · Rahime Ceylan¹ · Mesut Sivri² · Hasan Erdogan³

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Abstract Computed tomography (CT) scans usually include some disadvantages due to the nature of the imaging procedure, and these handicaps prevent accurate abdomen segmentation. Discontinuous abdomen edges, bed section of CT, patient information, closeness between the edges of the abdomen and CT, poor contrast, and a narrow histogram can be regarded as the most important handicaps that occur in abdominal CT scans. Currently, one or more handicaps can arise and prevent technicians obtaining abdomen images through simple segmentation techniques. In other words, CT scans can include the bed section of CT, a patient's diagnostic information, low-quality abdomen edges, low-level contrast, and narrow histogram, all in one scan. These phenomena constitute a challenge, and an efficient pipeline that is unaffected by handicaps is required. In addition, analysis such as segmentation, feature selection, and classification has

meaning for a real-time diagnosis system in cases where the abdomen section is directly used with a specific size. A statistical pipeline is designed in this study that is unaffected by the handicaps mentioned above. Intensity-based approaches, morphological processes, and histogram-based procedures are utilized to design an efficient structure. Performance evaluation is realized in experiments on 58 CT images (16 training, 16 test, and 26 validation) that include the abdomen and one or more disadvantage(s). The first part of the data (16 training images) is used to detect the pipeline's optimum parameters, while the second and third parts are utilized to evaluate and to confirm the segmentation performance. The segmentation results are presented as the means of six performance metrics. Thus, the proposed method achieves remarkable average rates for training/test/validation of 98.95/99.36/99.57% (jaccard), 99.47/99.67/99.79% (dice), 100/99.91/99.91% (sensitivity), 98.47/99.23/99.85% (specificity), 99.38/99.63/99.87% (classification accuracy), and 98.98/99.45/99.66% (precision). In summary, a statistical pipeline performing the task of abdomen segmentation is achieved that is not affected by the disadvantages, and the most detailed abdomen segmentation study is performed for the use before organ and tumor segmentation, feature extraction, and classification.

✉ Hasan Koyuncu
hasankoyuncu@selcuk.edu.tr

Rahime Ceylan
rpektatli@selcuk.edu.tr

Mesut Sivri
drmesutsivri@gmail.com

Hasan Erdogan
dr.hasanerdogan@gmail.com

¹ Engineering Faculty, Department of Electrical and Electronics Engineering, Selcuk University, 42250 Konya, Turkey

² Ankara Child Health and Disease Hematology Oncology Training and Research Hospital, Radiology Clinic, University of Health Sciences, Ankara, Turkey

³ Konya Training and Research Hospital, Radiology Clinic, University of Health Sciences, Konya, Turkey

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Introduction

Computed tomography (CT) has a wide range of uses in medicine. As a type of CT, abdominal CT scans are utilized to find

abnormalities around or inside of abdominal organs such as the liver, spleen, colon, pancreas, kidney, adrenal, and stomach. In this area, valuable solutions and hybrid structures are designed using effective algorithms for segmentation, feature extraction, and classification tasks.

In medical image analysis, abdominal CT scans can contain several disadvantages during abdomen-based processes; these disadvantages can be defined as insufficient edge information, effect of the bed section, writing in the scan, low contrast, narrow histogram, and proximity between the edges of the abdomen and the CT. Herein, the most important one at the forefront is the low-quality edges that can preclude accurate segmentation. The second most important handicap is the bed section, which can affect the results of segmentation, feature extraction, and classification. During these operations, other disadvantages (low contrast, narrow histogram, and writing in the CT scan) can also change the ability of a computer-aided diagnosis (CAD) system in terms of integrability.

Abdomen segmentation is defined with various different names in literature. Koss et al. [1] realized the segmentation of abdomen parts including *skin segmentation*, which specifies the outer edge of the abdomen. In their study, a segmentation process surrounding the outer edge of the abdomen was not directly identified, but the skin part including the colon was segmented with 91% accuracy. Atlas-based procedures were proposed to segment the different parts of the abdomen [2–5]. However, neither the contours of the abdomen nor the direct obtainment of the abdomen atlas was realized to prepare the data for further stages. Rangayyan et al. [6] realized the landmarking of abdomen, but the abdomen part was so brilliant in their study that it could be obtained with a simple binarization process. Xu et al. [7] designed the augmented active shape models (AASM) for segmentation of the abdomen and spinal cord. According to the visual results in [7], there were no low-quality edged abdominal images or bed section in the CT scans. As seen in the literature, very few studies touch upon the subject of abdomen segmentation, whether directly or indirectly. Besides, no detailed pipeline or technique is proposed to obtain the abdomen from CT images for different situations, which can cause information loss in tumor- or organ-based CAD applications.

The rest of the paper is organized as follows: Section 2 includes comprehensive explanations of the methods and proposed pipeline. Parameter settings are presented with their reasons in Section 3, and the experiments are realized using well-known statistical metrics for evaluating the performance of a pipeline. The necessities of pipeline operators are examined regarding whether the operators are essential. A visual representation is settled to prove the pipeline's efficiency. Besides, the pipeline performance is examined on training, test, and validation datasets. Finally, Section 4 contains concluding remarks.

Methods

The basic aim of this study is to obtain the abdomen for both low-quality and qualified edged abdomen images. This requires forming morphological and spatial transforms and the pipeline should be registered as unaffected by the disadvantages of the nature of CT scans. Concerning this, several efficient approaches (both formed by us and taken from the literature) are used to design a robust pipeline. Herein, the pipeline's name (AbSeg) is defined using the abbreviation *Abdomen Segmentation* process.

1. Largest object finder
2. Image dilation
3. Median filter
4. Gradient magnitude
5. Contrast-limited adaptive histogram equalization (CLAHE)
6. Spatial fuzzy C-means clustering
7. Morphological closing
8. Zerocross eliminator

In this section, the algorithms used are defined in four subparts: (1) well-known morphological algorithms, (2) proposed simple morphological approaches, (3) SFCM, (4) proposed pipeline. Herein, the techniques are presented in an obvious and brief manner to prevent monotony and provide a better understanding.

Well-Known Morphological Algorithm

Image Dilation *Dilation* signifies a morphological process that concretizes the edges and other elements of objects in an image. It enlarges (thickens) objects according to the filter (structuring element) [8]. These elements can be chosen as *disk*, *line* (with a different angle), *diamond*, etc. On grayscale images, *dilation* is defined as in Eq. (1) [8]. In Eq. (1), A and B are respectively the original image and structuring element, D_B symbolizes the domain of structuring element B , and $A(x,y)$ is presumed to be $-\infty$ outside the image's domain.

$$(A \oplus B)(x, y) = \max \left\{ A(x-x', y-y') + B(x', y') \mid (x', y') \in D_B \right\} \quad (1)$$

Morphological Closing *Closing* is a morphological process such as *dilation* that connects the gray values of objects in an image. In the morphological closing of grayscale images, the connection process is used to smooth the edges of objects. However, it can fill smaller areas than a structuring element and thus it is susceptible to high noise levels. As in the *dilation* process, *closing* uses the structuring elements *disk*, *line* (with

different angle), *diamond*, etc. On grayscale images, *closing* is defined as in Eq. (2) [8]. In Eq. (2), *closing* ($A \bullet B$) means the combination of dilation process ($A \oplus B$) and the erosion of B ($\ominus B$).

$$A \bullet B = (A \oplus B) \ominus B \quad (2)$$

Median Filter The median filter constitutes a nonlinear method that performs a smoothing/denoising process for objects in images [9]. During this process, the neighborhoods of pixels are considered to perform smoothing [9]. Herein, the new intensity of a pixel is defined as the median of its neighborhoods.

Gradient Magnitude *Gradient* means the generalized version of the derivative and stands for the direction of the largest increase of function [10]. The gradient magnitude (GM) refers to the slope of the graph in the direction that owns the largest increase [10]. GM is generally utilized to determine the direction of objects in an image, and this feature brings GM to the forefront for applications based on edge detection.

Contrast-Limited Adaptive Histogram Equalization

Adaptive histogram equalization (AHE) improves the irregular contrast distribution by transforming each pixel with a function derived from a neighborhood region. In its basic form, the transformation function is chosen as the histogram of a square surrounding the pixel [11]. Contrast-limited adaptive histogram equalization constitutes an improved contrast enhancement technique using histogram features, and it differs from the general *Histogram Equalization with contrast limiting* process [11]. At this point, *Contrast Limiting* is utilized to prevent the amplification of the noise level that arises from the contrast level increase [11].

The Proposed Simple Morphological Approaches

In this study, the two simple morphological approaches we formed were processed to ease the segmentation of the abdomen and improve the abdomen segmentation performance.

Largest Object Finder

Largest object finder (LOF) reveals the largest volume by utilizing the summation of rows and columns. After summation, the largest grayscale changes are found in the vertical and horizontal vectors, and the rectangular volume including the abdomen is obtained by utilizing the coordinates of these largest gray values. Two handicaps are eliminated through the LOF approach: (1) the unnecessary parts belonging to an irrelevant region and (2) the rows and columns including zero values. Herein, the unnecessary parts stand for the areas

including the appearance of the bed section and the writings in the scan.

The pseudocode of LOF is presented in Table 1. The first process of LOF is contrast enhancement using logarithmic nonlinear stretching, as shown in Eq. (3) [8].

$$g = b^* \log(af + 1) \quad (3)$$

In Eq. (3), g and f are respectively the contrast enhanced and original images, a and b are constants adjusting the contrast level.

LOF is used to prevent the negative effects of bed section and the writings that can influence edge detection for the abdomen. In addition, the LOF algorithm can effectively remove the bed section and the writings that do not intersect with the abdomen in the vertical and horizontal directions. However, the handicap of LOF is revealed as the adjacent segmentation of the abdomen and bed section as one part if the appearance of the bed section surrounds the bottom of the abdomen; this situation is shown in Fig. 1.

In Fig. 1, the area between the red arrows (A3) is cleaned, but other parts (bed sections A2 and A1) cannot be removed from the CT scan because the horizontal vector obtained at the bottom of the image and the down sight of the vertical vector include a continuous gray change. Concerning this, the LOF algorithm can only clean A3 because of the (close) surrounding bed section.

In other parts of the pipeline, we try to eliminate this handicap for the obtainment of the abdomen. In addition, LOF is added to the pipeline to guarantee the segmentation of the abdomen with the other efficient parts that are also prepared to minimize the effect of the aforementioned handicaps. Some of the disadvantages can be eliminated at this point, or the

Table 1 Pseudocode of the LOF algorithm

Pseudocode of LOF
Contrast enhancement with nonlinear stretching (logarithmic transformation—Eq. (3))
Find the summation of an image in the vertical and horizontal directions (obtaining two vectors)
For $i = 1$ to the length of the horizontal vector
Count the nonzero values and save the coordinates until the end of the vector
End
For $i = 1$ to the length of the vertical vector
Count the nonzero values and save the coordinates until the end of the vector
End
Calculate the largest lengths in both the horizontal and vertical vectors
Find the largest volume using the coordinates of the largest lengths
Assign zero to the unnecessary parts that are outside the largest volume

Fig. 1 Vector definition of LOF in a challenging CT image

necessary operators can prevent the disadvantages influencing the segmentation results.

Zerocross Eliminator

The zerocross eliminator (ZE) fulfills the cleaning of rows and columns in which all intensities equal zero; for this, it uses the summation of the rows and columns. After the summation process, ZE moves forward to the gray values from the middle of the outer edges of the image in four directions. Thus, it eliminates the zero values that came from the rest of the pipeline, meaning that ZE removes unnecessary zeros, sensitively; this situation is presented in Fig. 2.

Figure 2 shows that the ZE algorithm eliminates the zeros in the direction shown with a red arrow, since the other parts include nonzero intensity levels. The pseudocode of the ZE algorithm is as shown in Table 2.

Fig. 2 Elimination of zeros by the ZE algorithm

Spatial Fuzzy C-means Clustering

A fuzzy C-means (FCM) algorithm constitutes a clustering method that divides the data into one or more classes [12, 13]. FCM constitutes an iterative structure that obtains partitions by minimizing the objective in Eq. (4) [12, 13].

$$J = \sum_{j=1}^N \sum_{i=1}^c u_{ij}^m \|x_j - v_i\|^2 \quad (4)$$

In Eq. (4) [12, 13], u_{ij} symbolizes the membership of x_j belonging to the i_{th} cluster, c is the number of clusters, v_i is the center of the i_{th} cluster, and m is a constant parameter. Herein, the minimization of the cost function is obtained when the pixels close to the center of cluster are handled.

In FCM, u_{ij} and v_i are respectively updated according to Eqs. (5) and (6) [12].

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|} \right)^{2/(m-1)}} \quad (5)$$

$$v_i = \frac{\sum_{j=1}^N u_{ij}^m x_j}{\sum_{j=1}^N u_{ij}^m} \quad (6)$$

Spatial FCM (SFCM) is inspired using the spatial information beyond the neighbor pixels, since these pixels involve similar features. For this, the spatial function should be defined as in Eq. (7) [12].

$$h_{ij} = \sum_{k \in H(x_j)} u_{ik} \quad (7)$$

In Eq. (7), $H(x_j)$ is a square window on pixel x_j , h_{ij} stands for the probability of whether x_j belongs to the i_{th} cluster. Herein, the value of h_{ij} is higher if most of its neighbor pixels pertain to the same cluster with x_j . Spatial information is added to general FCM as in Eq. (8) [12].

$$u'_{ij} = \frac{u_{ij}^p h_{ij}^q}{\sum_{k=1}^c u_{kj}^p h_{kj}^q} \quad (8)$$

Table 2 Pseudocode of the ZE algorithm

ZE pseudocode
Find the summation of the image in the vertical and horizontal directions (obtain two vectors)
For $i = 1$ to the length of the <i>horizontal vector</i>
Count zeros from the <i>left</i> side of the image and save the coordinates until a gray value is met
End
For $i = 1$ to the length of the <i>horizontal vector</i>
Count zeros from the <i>right</i> side of the image and save the coordinates until a gray value is met
End
For $i = 1$ to the length of the <i>vertical vector</i>
Count zeros from the <i>up</i> side of the image and save the coordinates until a gray value is met
End
For $i = 1$ to the length of the <i>vertical vector</i>
Count zeros from the <i>down</i> side of the image and save the coordinates until a gray value is met
End
Find the last coordinates that are the closest points to the edges using the saved coordinates
Obtain nonzero output using these last coordinates

In Eq. (8), p and q are control parameters and the whole process prevents the noise affecting the clustering results by utilizing the neighbor intensities and weights [12].

Proposed Pipeline (AbSeg)

AbSeg is an efficient pipeline that can be used on low-quality and qualified edged abdomen images. The proposed pipeline is not affected by *the appearance of the bed section* close to the bottom of the abdomen. *The small writing* at the corner of the images is also removed by wise additions (operators) in pipeline. Besides, AbSeg can be used on images that include *low contrast* and on scans owing to a *narrow histogram*. The flowchart of the pipeline is as shown in Fig. 3.

As seen in Fig. 3:

- The largest volume is obtained for the first part of the pipeline using the LOF algorithm, and the unnecessary parts (appearance of the bed section in CT, and writings above and below the abdomen) are removed. Herein, it should be defined that the bed section and the writings can be removed by simple thresholding techniques. However, this situation can lead to distortion on high-intensity pixels inside organs and other tissues. In AbSeg, the LOF algorithm is utilized to obtain the largest area (abdomen) without any loss for intensity values.
- The LOF algorithm involves two handicaps on some CT scans: (1) the bed appearance surrounding the abdomen

and (2) the sensitivity to the noise that occurs at the edge sights of the CT scan. Therefore, other parts of AbSeg stay necessary for the optimal segmentation of the whole abdomen. Herein, every part is used to eliminate one or more handicaps that occur in the CT scan.

- In the second part, *image dilation* is realized to obtain the outer edges of the abdomen for low-quality (discontinuous) edges. For this, *image dilation* is performed using the *line* type-structuring element, and 36 different directions ($0^\circ, 5^\circ, \dots, 175^\circ$) are used to concretize the abdomen's outer edge.
- In the third part, a *median filter* is used to smooth the thickened edges obtained through *image dilation*. In addition, it reduces the blurry vision around the edges.
- In the fourth part, the *gradient magnitude* is obtained to discover the outer edges of the abdomen.
- In the fifth part, *morphological closing* is fulfilled to combine the different intensity (grayscale) values inside the abdomen.
- Afterwards, CLAHE is processed to improve the contrast features of the image (output of *morphological closing*) in case the CT's contrast level seems poor.
- After CLAHE, the SFCM algorithm is run to segment the abdomen part from the background. In the output of SFCM, a binary image is ensued that includes gaps inside the abdomen. Herein, the *filling* process is implemented to fill the connected components.
- Thereafter, the coordinates of the rectangle enclosing the abdomen are detected using the largest filled region in the binary image.
- In the 10th part, ZE is operated to remove the rows and columns in which all intensities equal zero. In the last part, the abdomen image is reorganized by the *scaling* process (550×700).

As seen in AbSeg, necessary operators are processed to guarantee the segmentation of the abdomen on different characterized abdominal CT images. Parameter settings and experiments are presented in the next section.

Results and Discussion

This section first presents the parameter settings and problems, and then the experiments are investigated and interpreted in detail. For this, trials were implemented in Matlab R2015b on a personal computer with 2.60 GHz CPU and 6 GB RAM running Windows 8.

For performance evaluation, the used data was divided into three groups: training (16 images), test (16 images), and validation (26 images). Training and test images were provided by Siemens Somatom Definition Flash CT. In this device, the reconstruction package is advanced modeled iterative

Fig. 3 Flowchart of AbSeg

reconstruction (ADMIRE) and used the industry's first raw-data-based iterative reconstruction method (SAFIRE). Validation data was taken from The Cancer Imaging Archive (TCIA) [14, 15]. In the validation dataset, chest and pelvic CT images were added to the trials beside the abdominal CT images.

Sensitivity, specificity, precision, classification accuracy (CA), dice, and jaccard were used as performance metrics for a detailed examination [16–23]. In Eq. (9–14), TP, TN, FP, and FN, respectively, symbolize the number of true-positive, true-negative, false-positive, and false-negative results.

$$\text{Sensitivity} = TP / (TP + FN) \quad (9)$$

$$\text{Specificity} = TN / (TN + FP) \quad (10)$$

$$\text{Precision} = TP / (TP + FP) \quad (11)$$

$$CA = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

$$\text{Dice} = (2 * TP) / ((2 * TP) + FP + FN) \quad (13)$$

$$\text{Jaccard} = TP / (FN + FP + TP) \quad (14)$$

Parameter Settings of AbSeg

AbSeg includes coherent operators that can regulate one or more problem. At this point, AbSeg's parameter settings play an important role in the elimination of handicaps for accurate abdomen segmentation. In other words, parameter settings are

performed according to the problems based on the abdomen's features (shape, intensity, structure, etc.). Some of these are as shown in Figs. 4 and 5.

Figure 4 a and b show an abdomen image close to the edges of the scan. Figure 4 a shows the *closing* process attaching the abdomen to the edges of the CT scan in which the structuring element is chosen as *disk*. Figure 4 b presents the *closing* that includes two *line*-type structuring elements that combine the results with angles 15 and 165° to prevent adhesion around the right and left edges of the abdomen. As seen in Fig. 4 a and b, it is explicit that the structuring element should be properly chosen for abdomen images in which the outer edges of the abdomen stay close to the edges of the CT scan.

Figure 4 c and d handle the images that include the appearance of the bed section close to the bottom of the abdomen. Figure 4 c shows the results with *disk* type closing, while Fig. 4 d presents the *closing* results obtained by two *line*-type structuring elements combining the results with angles 15 and 165°. Figure 4 c and d reveal that if the structuring element is not correctly chosen, the gap between the bed section and the abdomen can cause information loss for abdomen segmentation.

As seen in Fig. 4, the type of structuring element plays a key role in eliminating the negative effects of close CT edges and close bed appearance to the abdomen. Besides, the other types of structuring elements (diamond, square, etc.) ruin the

Fig. 4 Problems and accomplishments for *closing*

Fig. 5 Dilation problem and accomplishment

obtainment of the abdomen. Experiments have shown that the *line*-type structuring element performs a better *closing* process because it uses two opposite angles (15° and 165°) that are the optimum angles for abdomen detection.

As seen in Fig. 5, the outer edges of the abdomen involve unconnected parts and should be linked together. In Fig. 5 a and b, the *dilation* process is realized to reveal the outer edges of the abdomen. Figure 5 a presents *dilation* using the *disk*-type structuring element, but this process cannot reveal the abdomen's unconnected edges. Figure 5 b shows *dilation* using the *line*-type structuring element. The output image is obtained by summing the outputs of *line*-type dilated images using 36 different angles ($0^\circ, 5^\circ, \dots, 175^\circ$) that strengthen the outer edges of the abdomen and complete the unconnected parts. Herein, suitable types of structuring element constitute an indispensable need for the implementation of edge detection.

The constants in LOF (*a* and *b*) are adjusted to obtain contrast enhanced-distinct edges and to form a clear input to the LOF algorithm. For the size of median filter, optimum kernel is revealed as [5 5], since smaller values cannot remove noisy and blurry vision. In addition, the larger size can cause the loss of edge information. The SFCM threshold number is chosen as “1” and the proposed pipeline is designed according to this rule.

As seen in the explanations stated above, the optimum parameter values are investigated and ensued according to the abdomen segmentation requirements. Similarly, all operators and the used parameters of operators are examined to achieve the optimal parameter values and operation conditions. Thus, the parameter settings of AbSeg are as shown in

Table 3. Herein, these settings are performed by using the training dataset (16 abdominal CT images).

Experimental Results

In experiments, 58 CT images were utilized to evaluate the performance of AbSeg. These images include some parts of the following features: low-quality abdomen edges, appearance of bed section and writings, low contrast, narrow histogram, and close abdomen edges to the edges of the scans. In performance evaluation, the results are obtained for the segmentation of the rectangle (ROI) surrounding the abdomen.

In the first part of the experiments, the parameter settings and training performance were obtained using the training dataset (16 CT scans) using six statistical metrics (dice, jaccard, etc.). In Table 4, the segmentation results of the rectangles enclosing the abdomen are realized, and the results are obtained by comparing the rectangle template with the output of AbSeg.

As seen in Table 4, AbSeg achieves reliable segmentation results with high scores for all performance metrics. This means that AbSeg performs the task in different circumstances by obtaining high success rates (especially for dice and jaccard) of approximately 99%.

In Table 5, the importance of operators is clarified by extracting the parts, and by running the system on different images. Tables 6 and 7 compare the performance comparisons of three thresholding techniques in terms of obtaining the abdomen section for low-quality and qualified edged abdomens. Higher rates are italicized in the tables.

As seen in Table 5, every section benefits from segmentation, and these operators remain essential for an accurate segmentation process. In addition, the percentage differences between with/without parts prove the efficiency of operators in AbSeg. At this point, the most important sections are presented in Table 5, meaning that other parts do not work for all images. This means that other parts are operated for the elimination of different problems. In Table 5, Arterial_12 stands for the image containing a low-quality (edged) abdomen.

In Tables 6 and 7, performance comparison is presented using the outputs of binarization, Otsu [24], and SFCM approaches.

Table 3 Optimum parameter values

AbSeg section	Parameter name	Optimum value or range
LOF	Constants (<i>a</i> and <i>b</i> in Eq.(3))	<i>a</i> = 10, <i>b</i> = 1
Image dilation	Length of lines	3
	Angle of lines	$0^\circ, 5^\circ, \dots, 175^\circ$
Median filter	Size	[5 5]
Image closing	Length of lines	23
	Angle of lines	$15^\circ, 165^\circ$
SFCM	Threshold number	1 (two classes)

Table 4 Performance evaluation of AbSeg on the training dataset

Images	Jaccard	Dice	Sensitivity	Specificity	CA	Precision
Arterial_1	99.4741	99.7364	100	98.4158	99.5798	99.5945
Arterial_2	98.7221	99.3569	100	96.8136	99.0795	98.7221
Arterial_3	99.2613	99.6293	100	99.1291	99.5987	99.2613
Arterial_4	98.8633	99.4284	100	98.6689	99.3831	98.8633
Arterial_5	99.0488	99.5221	100	98.8644	99.4797	99.0488
Arterial_6	98.8743	99.4339	100	98.8006	99.4159	98.8743
Arterial_7	99.1987	99.5977	100	99.1811	99.5442	99.3731
Arterial_8	99.5635	99.7812	100	99.3070	99.6972	99.6914
Arterial_9	98.8133	99.4031	100	97.5640	99.1956	98.8133
Arterial_10	99.2672	99.6323	100	98.8434	99.5494	99.2672
Arterial_11	98.7896	99.3911	100	98.3925	99.3047	98.7896
Arterial_12	98.9234	99.4588	100	98.9337	99.4227	99.0667
Arterial_13	98.4711	99.2297	100	98.0364	99.1329	98.4711
Arterial_14	99.0381	99.5167	100	98.8736	99.4784	99.0381
Arterial_15	99.0081	99.5016	100	97.6150	99.2945	99.0081
Arterial_16	97.8232	98.8996	100	98.1300	98.9839	97.8232
Mean	<i>98.9463</i>	<i>99.4699</i>	<i>100</i>	<i>98.4731</i>	<i>99.3838</i>	<i>98.9816</i>

The best results are presented as italicized numbers

Table 5 Performance evaluation of the AbSeg sections

Performance without sections (with/without)	Image	Jaccard	Dice	CA
Image dilation	Arterial_12	<i>98.92/82.09</i>	<i>99.46/90.16</i>	<i>99.42/90.49</i>
Clarification and denoising (median filter)	Arterial_16	<i>97.82/96.72</i>	<i>98.90/98.33</i>	<i>98.98/98.45</i>
Obtainment of gradient magnitude	Arterial_13	<i>98.47/97.83</i>	<i>99.23/98.90</i>	<i>99.13/98.76</i>
Morphological closing	Arterial_12	<i>98.92/81.77</i>	<i>99.46/89.97</i>	<i>99.42/90.32</i>
Contrast-limited adaptive histogram equalization	Arterial_12	<i>98.92/84.95</i>	<i>99.46/91.86</i>	<i>99.42/91.99</i>
Zerocross cleaning (ZE)	Arterial_5	<i>99.05/98.90</i>	<i>99.52/99.45</i>	<i>99.48/99.40</i>

The best results are presented as italicized numbers

As seen in Table 6, SFCM always outperforms Otsu and binarization algorithms in terms of achieving better dice, jaccard, and CA rates on images including low-quality edged abdomen. As seen in Table 7, the performance of SFCM and Otsu is the same for qualified edged abdomens, and their performance draws a graph that remains better than the binarization process. Consequently, it is inferred that the SFCM algorithm seems the best choice, since it achieves optimum results for both low-quality and qualified edged abdomen images.

After trials based on the training dataset, the proposed pipeline was implemented on test data that was completely diverse from the training set. Table 8 shows the performance evaluation of AbSeg for test data.

As seen in Table 8, AbSeg presents a remarkable performance by achieving a 99.5% average rate for six different metrics and it obtains better results for the test dataset than the training set. The

average rates for training/test were 98.95/99.36% (jaccard), 99.47/99.67% (dice), 100/99.91% (sensitivity), 98.47/99.23% (specificity), 99.38/99.63% (classification accuracy), and 98.98/99.45% (precision). In other words, AbSeg proved its efficiency by increasing the rates of jaccard, dice, specificity, CA, and precision on a different dataset than that utilized in the parameter settings.

Figure 6 shows the output of pipeline on different sections to demonstrate the visual results of different characterized images.

As seen in Fig. 6, the first image includes an abdomen scan in which the edges of the abdomen are very close to the edges of the scan. The second image involves the appearance of a bed section in the CT surrounding the bottom side of the abdomen and the third image includes an abdomen in which the edges of the abdomen are discontinuous.

As seen in the visual results, morphological processes fulfill their tasks without any disruptive effect on the abdomen,

Table 6 Performance comparison of the three techniques on low-quality edged abdomen

Thresholding approaches (Arterial_12)	Jaccard	Dice	Sensitivity	Specificity	CA	Precision
Binarization	98.40	99.19	99.85	98.33	99.14	98.54
Otsu	93.89	96.85	94.36	99.44	96.74	99.48
Spatial fuzzy C-means clustering	<i>98.92</i>	<i>99.46</i>	<i>99.85</i>	<i>98.93</i>	<i>99.42</i>	99.07

The best results are presented as italicized numbers

Table 7 Performance comparison of the three techniques on qualified edged abdomen

Thresholding approaches (Arterial_4)	Jaccard	Dice	Sensitivity	Specificity	CA	Precision
Binarization	97.89	98.93	100	97.50	98.84	97.89
Otsu	<i>98.86</i>	<i>99.43</i>	<i>100</i>	<i>98.67</i>	<i>99.38</i>	<i>98.86</i>
Spatial fuzzy C-means clustering	<i>98.86</i>	<i>99.43</i>	<i>100</i>	<i>98.67</i>	<i>99.38</i>	<i>98.86</i>

The best results are presented as italicized numbers

Table 8 Performance evaluation of AbSeg on the test dataset

Images	Jaccard	Dice	Sensitivity	Specificity	CA	Precision
Arterial_17	99.3226	99.6602	100	99.2613	99.6454	99.3226
Arterial_18	99.5436	99.7713	100	99.1761	99.7054	99.5436
Arterial_19	99.4610	99.7297	100	99.0167	99.6506	99.4610
Arterial_20	97.6528	98.8125	100	97.1643	98.6991	97.6528
Arterial_21	98.5149	99.2519	98.8342	99.5450	99.1299	99.6731
Arterial_22	99.6077	99.8035	100	99.0005	99.7175	99.6077
Arterial_23	99.3692	99.6836	100	99.3760	99.6853	99.3692
Arterial_24	99.5604	99.7797	100	99.4773	99.7606	99.5604
Arterial_25	99.5505	99.7747	100	99.4889	99.7603	99.5505
Arterial_26	99.5392	99.7691	100	99.3729	99.7337	99.5392
Arterial_27	99.6599	99.8297	100	99.5762	99.8110	99.6599
Arterial_28	99.4008	99.6995	100	99.3165	99.6797	99.4008
Arterial_29	99.6809	99.8402	99.8988	99.6017	99.7935	99.7817
Arterial_30	99.6735	99.8365	100	99.5579	99.8119	99.6735
Arterial_31	99.5726	99.7858	99.8829	99.4332	99.7234	99.6890
Arterial_32	99.6976	99.8486	100	99.2685	99.7856	99.6976
Mean	<i>99.3629</i>	<i>99.6798</i>	<i>99.9135</i>	<i>99.2271</i>	<i>99.6308</i>	<i>99.4489</i>

The best results are presented as italicized numbers

and this situation is confirmed by the output images. Besides, the effectiveness of AbSeg can be seen with regard to its

operation as immune to different handicaps. In other words, the optimum and statistical structure can be obtained for

Fig. 6 Visual results obtained from different AbSeg sections (from left to right: original image, dilated image, closed image, output of SFCM, and output of AbSeg)

Fig. 7 The different types of CT image used in the validation set

changeable situations that can prevent the abdomen's segmentation.

In the last part of the visual results, every image is resized to 550×700 since it is revealed as the best ratio in trials between the abdomen's vertical and horizontal structure.

After training, tests, and visual results, a validation process is performed to confirm the performance of AbSeg on a new data taken from The Cancer Imaging Archive (TCIA) [14, 15]. For this, 26 CT images were randomly chosen from a dataset that included different types of scans (PET/CT, chest CT, abdominal CT, and pelvis CT images). The data used consists of 12 abdomi-

nal CTs, 11 chest CTs, and three pelvis CT images. Herein, the performance of AbSeg is evaluated on chest CT and pelvis CT images besides abdominal-based trials, for whether it can be utilized on the segmentation of similar (ellipsoid) shaped ROIs (chest CT and pelvis CT images).

In the training and test images, the used data is 852×852 , whereas it is chosen as 1920×1080 in the validation dataset. At this point, the image resolution is examined to reveal whether it positively affects the segmentation results. Figure 7 shows the utilized image types, Table 9 shows the results of the AbSeg pipeline on validation data, Table 10

Table 9 Performance evaluation of AbSeg in the validation dataset

Images	Jaccard	Dice	Sensitivity	Specificity	CA	Precision	Kind of CT Scan
Image_1	99.6617	99.8306	100	99.8193	99.8821	99.6617	Abdomen
Image_2	99.4603	99.7294	100	99.7984	99.8530	99.4603	Abdomen
Image_3	99.7768	99.8883	100	99.9639	99.9689	99.7768	Abdomen
Image_4	99.6630	99.8312	99.8812	99.8508	99.8631	99.7813	Pelvis
Image_5	99.4940	99.7464	99.8930	99.8226	99.8442	99.6001	Chest
Image_6	99.6902	99.8448	99.6902	100	99.9374	100	Abdomen
Image_7	99.5080	99.7534	99.6493	99.9317	99.8400	99.8578	Chest
Image_8	99.5626	99.7808	100	99.8857	99.9093	99.5626	Chest
Image_9	99.2873	99.6424	99.7758	99.9058	99.8849	99.5094	Pelvis
Image_10	99.7761	99.8879	100	99.8537	99.9115	99.7761	Chest
Image_11	99.6485	99.8239	99.8713	99.8541	99.8609	99.7766	Chest
Image_12	99.6514	99.8254	100	99.8301	99.8857	99.6514	Abdomen
Image_13	99.6115	99.8054	100	99.8017	99.8685	99.6115	Abdomen
Image_14	99.5779	99.7885	99.8856	99.7638	99.8166	99.6916	Chest
Image_15	99.6063	99.8028	99.8924	99.9045	99.9015	99.7133	Chest
Image_16	99.4921	99.7454	99.6810	99.9642	99.9192	99.8099	Abdomen
Image_17	99.3393	99.6685	99.8051	99.8967	99.8801	99.5324	Abdomen
Image_18	99.5663	99.7827	100	99.6938	99.8202	99.5663	Chest
Image_19	99.5410	99.7700	99.8667	99.8052	99.8281	99.6735	Chest
Image_20	99.5526	99.7758	99.8819	99.7938	99.8276	99.6699	Chest
Image_21	99.6389	99.8191	100	99.8450	99.8914	99.6389	Abdomen
Image_22	99.4790	99.7388	100	99.7879	99.8491	99.4790	Pelvis
Image_23	99.5120	99.7554	99.8534	99.8273	99.8360	99.6576	Chest
Image_24	99.6653	99.8324	100	99.8144	99.8804	99.6653	Abdomen
Image_25	99.4734	99.7360	100	99.7937	99.8516	99.4734	Abdomen
Image_26	99.6770	99.8382	100	99.8031	99.8775	99.6770	Abdomen
Mean	99.5736	99.7863	99.9087	99.8466	99.8726	99.6644	–

Table 10 Average performance of AbSeg for different types of CT images

Kind of CT scan	Jaccard	Dice	Sensitivity	Specificity	CA	Precision
Abdomen (12 images)	99.5948	99.7970	99.9314	99.8609	99.8913	99.6632
Chest (11 images)	99.5768	99.7880	99.8903	99.8306	99.8542	99.6859
Pelvis (3 images)	99.4764	99.7375	99.8857	99.8482	99.8657	99.5899

Table 11 Performance evaluation of AbSeg for different resolutions

Dataset	Jaccard	Dice	Sensitivity	Specificity	CA	Precision
Training (16 images)	98.9463	99.4699	100	98.4731	99.3838	98.9816
Test (16 images)	99.3629	99.6798	99.9135	99.2271	99.6308	99.4489
Validation (26 images)	99.5736	99.7863	99.9087	99.8466	99.8726	99.6644

Table 12 Performance evaluation of AbSeg sections

Method	Task	Method	Dice (%)	CA (%)
Koss et al. [1]	Skin and colon segmentation	Hopfield Neural Network (HNN)-based hybrid approach	–	91
Xu et al. [7]	Abdomen wall segmentation	Multi-atlas label fusion	89	–
This study	Abdomen segmentation	AbSeg	99.64	99.61

presents the average performance obtained for different types of CT image, and Table 11 reveals the average performance on the data for different resolutions (training and test validation).

In Fig. 7, the abdomen, chest, and pelvis areas change as they are diverse from one another, and the shape of the ROIs seems non-proportional. As it differs from the training and test datasets, the validation set includes high-resolution CT images. Herein, PET/CT images are not included in the validation data because the segmentation operation of these images constitutes another qualified paper because PET/CT images include the arm parts of patients, which prevent the accurate segmentation of ellipsoid ROIs.

According to Table 10, the segmentation performance of AbSeg remains remarkable for the abdomen and it can segment the abdomen better than the chest and pelvis CT images for all metrics. In future evaluation, its usage may be extended to chest and pelvis CT images in terms of including an ellipsoid ROI as in abdomen CT images, but the amount of data should be increased to generalize the performance of AbSeg to chest and pelvis CT images. Currently, it can be seen that AbSeg can segment abdominal CT images with a high success rate, and its performance seems remarkable for similar shaped ROIs and the chest and pelvis areas.

Table 11 reveals that AbSeg performs the task of abdomen segmentation on different datasets with higher performance for approximately all metrics (except sensitivity) compared to trials realized on training and test datasets. It can be concluded here that the resolution quality directly affects the system's output, and a higher resolution is required to attain better segmentation results.

Conclusions

This study contains an efficient and statistical structure for the optimum segmentation of the abdominal region in CT images. According to the results, AbSeg performs the task of abdomen

segmentation under different handicaps that occur in abdominal CT images. Besides, it obtained very high segmentation results for the above six statistical metrics, with respective rates of 98.95, 99.2, and 99.57% for the training, test, and validation sets. Moreover, it was not affected by the appearance of the bed section, patient information, narrow histogram, poor contrast, or low-quality edges by processing sequential operators that eliminate the handicaps. In addition, AbSeg is designed using optimal operators and parameters for the segmentation of the abdominal region.

Table 12 shows the literature comparison of studies based on abdomen segmentation. Herein, it should be remembered that the results of AbSeg can be obtained on the segmentation of the rectangle surrounding the abdomen part. In other words, the results are based on a rectangle ROI that surrounds the abdomen, meaning that a higher performance is achieved in the event that the rectangle overlaps the edges of the abdomen.

In future work, we want to use AbSeg to detect and segment different types of tumors that can occur in the abdomen. Moreover, the usage of AbSeg will be extended to segment different regions in other scan types.

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References

1. Koss JE, Newman FD, Johnson TK, Kirch DL: Abdominal organ segmentation using texture transforms and a hopfield neural network. *IEEE T Med Imaging* 18:640–648, 1999
2. Zhou Y, Bai J: Multiple abdominal organ segmentation: an atlas-based fuzzy connectedness approach. *IEEE T Inf Technol B* 11: 348–352, 2007
3. Wachinger C, Fritscher K, Sharp G, Golland P: Contour-Driven Atlas-Based Segmentation. *IEEE T Med Imaging* 34:2492–2505, 2015
4. Xu Z, Burke RP, Lee CP, Baucom RB, Poulouse BK, Abramson RG, Landman BA: Efficient multi-atlas abdominal segmentation on

- clinically acquired CT with SIMPLE context learning. *Med Image Anal* 24:18–27, 2015
5. Dennis LSE: Automated Segmentation of Soft tissue in Abdominal CT scans. Dissertation, National University of Singapore, 2009
  6. Rangayyan RM, Banik S, Boag GS: Landmarking and segmentation of computed tomographic images of pediatric patients with neuroblastoma. *Int J Comput Ass Rad* 4:245–262, 2009
  7. Xu Z, Conrad BN, Baucom RB, Smith SA, Poulouse BK, Landman BA: Abdomen and spinal cord segmentation with augmented active shape models. *J Med Imag* 3:036002, 2016
  8. Gonzalez RC, Woods RE, Eddins SL: Digital image processing using MATLAB. New York: McGraw Hill Education, 2009
  9. Lim JS: Two-Dimensional Signal and Image Processing, Englewood Cliffs: Prentice-Hall, 1990
  10. Korn GA, Korn TM: Mathematical handbook for scientists and engineers: Definitions, theorems, and formulas for reference and review. Mineola: Courier Corporation, 2000
  11. Zuiderveld K: Contrast limited adaptive histogram equalization. In: Heckbert PS (Ed.), *Graphics gems IV*. San Diego: Academic Press Professional Inc., 1994, pp 474–485
  12. Chuang KS, Tzeng HL, Chen S, Wu J, Chen TJ: Fuzzy c-means clustering with spatial information for image segmentation. *Comput Med Imag Grap* 30:9–15, 2006
  13. Yang Y, Huang S: Image Segmentation by Fuzzy C-Means Clustering Algorithm with A Novel Penalty Term. *Comput Inform* 26:17–31, 2007
  14. Clark K, Vendt B, Smith K, Freymann J, Kirby J, Koppel P, Moore S, Phillips S, Maffitt D, Pringle M, Tarbox L, Prior F: The Cancer Imaging Archive (TCIA): Maintaining and Operating a Public Information Repository. *J Digit Imaging* 26:1045–1057, 2013
  15. Albertina B, Watson M, Holback C, Jarosz R, Kirk S, Lee Y, Lemmerrman J: Radiology data from the cancer Genome Atlas Lung Adenocarcinoma [TCGA-LUAD] collection. *Cancer Imaging Arch*, 2016. <https://doi.org/10.7937/K9/TCIA.2016.JGNIHEP5>
  16. Labatut V, Cherifi H: Accuracy measures for the comparison of classifiers. *arXiv: 1207.3790*, 2012
  17. Franklin SW, Rajan SE: Computerized screening of diabetic retinopathy employing blood vessel segmentation in retinal images. *Biocybern Biomed Eng* 34:117–124, 2014
  18. Sethi G, Saini BS: Computer aided diagnosis system for abdomen diseases in computed tomography images. *Biocybern Biomed Eng* 36:42–55, 2016
  19. Alivar A, Danyali H, Helfroush MS: Hierarchical classification of normal, fatty and heterogeneous liver diseases from ultrasound images using serial and parallel feature fusion. *Biocybern Biomed Eng* 36:697–707, 2016
  20. Lee H, Troschel FM, Tajmir S, Fuchs G, Mario J, Fintelmann FJ, Do S: Pixel-Level Deep Segmentation: Artificial Intelligence Quantifies Muscle on Computed Tomography for Body Morphometric Analysis. *J Digit Imaging*, 2017, pp 1–12
  21. Koyuncu H, Ceylan R: A hybrid tool on denoising and enhancement of abdominal CT images before organ & tumour segmentation. In: 37th IEEE International Conference on Electronics and Nanotechnology (ELNANO 2017). Kiev: IEEE, 2017, pp 249–254. <https://doi.org/10.1109/ELNANO.2017.7939757>
  22. Koyuncu H, Ceylan R: Elimination of White Gaussian Noise in Arterial Phase CT Images to Bring Adrenal Tumours into the Forefront. *Comput Med Imaging Graph*, 2017
  23. Koyuncu H, Ceylan R: Optic disc segmentation with Kapur-ScPSO based cascade multithresholding. In: *International Conference on Bioinformatics and Biomedical Engineering*. Cham: Springer, 2016, pp 206–215. https://doi.org/10.1007/978-3-319-31744-1_19
  24. Otsu N: Thresholds selection method form grey-level histograms. *IEEE T Syst Man Cyb* 9:62–66, 1979