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Automatic lung segmentation for large-scale medical image management

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Abstract Digital medical images assist specialists in improving their diagnostic efficiency and in treating diseases. For example, the chest Computed Tomography (CT) images help in diagnosing the lung disease. The chest CT scan generates multiple images of a patient's lung. The size of the medical imaging data has increased with the usage of medical images. In a picture archiving and communication system, large-scale medical images must be transmitted to specialists through either wired or wireless communications and retained in the archive. Hence, medical images have to be compressed, and there should be no damage to the Region of Interest (RoI) during compression. In order to protect the RoI, image segmentation is needed to detect RoI in medical images. Among the various image segmentation methods available, the method using Level-set is robust to irregular noises. However, the problems faced in using this method include manual input of the initial contour and slow performance speed. Inputting an initial contour to the Level-set that correctly fits the object's form helps in reducing the number of repetitions. This in turn helps in improving the segmentation performance speed.

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However, it is difficult for a user to input an appropriate initial contour. Therefore, this paper aims at providing a method to auto-configure the initial contour in the Level-set method. Multi-resolution analysis helps in reducing the pace of the auto-configuration process of the initial contour. In addition, the volume data of a CT image is used to prevent data loss that occurs during the MRA transformation process. Studies have confirmed that the proposed method facilitates drastic improve.

Keywords Medical image · Large-scale data management · RoI coding · Image segmentation · Level-set · Chest CT image · Initial contour

1 Introduction

Improvements in the performance of medical imaging equipment and the generation of high-resolution digital images aid computer image analysis in medical diagnosis and treatment of diseases. Several new modality (such as X-Ray, Computerized Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound (US), and Positron Emission Tomography (PET)) have emerged that aid in extracting or visualizing the information on organ tissues from the diagnostic tomographic images obtained from various medical imaging equipment. This has resulted in active progress of the convergence of medical and IT fields.

With the wider usage of medical images, the resolution, number, and size of medical images that can be obtained from one patient has increased. For example, micro-CTs are made up of data from 1,024 serial 1,024 × 1,024 pixels cross-sectional images [25]. The medical images that are becoming large-scale data create problems in transmission, storage, and data usage. This results in difficulties in quickly receiving and inspecting medical images by specialists when they diagnose or treat patients. Furthermore, in tracking a patient's illness using medical images, the specialist activates more than two medical images on one screen to compare the changes in the illness. In order to make the comparisons easy, large-scale data management is needed. Data compression is necessary for effective management of large medical images. As a result, the Joint Photographic Experts Group 2000 (JPEG2000) used in digital imaging and communications in the field of medicine supports Region of Interest (RoI) coding in order to compress the data without damaging the RoI [1]. However, RoI coding does not include a method for extracting RoI. In order to extract the RoI from a medical image, the medical image must be segmented. But the accuracy of classifying and discriminating tissues found in the medical images of a complex anatomical structure relies on the analytical skill of the specialists involved in the process. Specialists with identical skill-sets tend to classify or discrimination tissues of a particular image in a different fashion. Furthermore, large-sacle medical images are problematic in that they increase the number of images that one specialist has to analyze. Rettman et al. confirmed that semiautomatic segmentation with computers improves the performance of image segmentation on a medical image dataset by 4–8 h to 45 min compared to manual segmentation [22]. As such, a fast and accurate medical image processing method using a computer helps in solving this issue.

Image segmentation is the first and the most important task of this method [13, 20]. Several studies on to this task have been undertaken with utmost interest. Image segmentation is followed by image registration, quantification, visualization and lesion detection. Due to the complexities in the structure of the organs of the human body and similarities in their biological characteristics, it is difficult to conduct the medical image segmentation process [22, 9].

Level-set is preferred over other medical segmentation methods, as it is robust to the impact of irregular characteristics including noise [15]. However, a Level-set requires the user to manually input the initial contour. On the one hand, an inappropriate configuration of the initial contour tends to decline the segmentation performance and the performance speed. On the other hand, an appropriate configuration of the initial contour in the Level-set helps in reducing the number of repetitive computation and in declining the performance time. However, it is impossible for a user to enter the initial contour that would fit the object's form and to configure similar quality of initial contour for all images. Therefore, this paper proposes Multi-resolution analysis Level-set (MLevel-set) which auto-configures the initial contour for a Level-set method. This method does not require any additional input by the user and it also helps in improving the performance speed. The MLevel-set helps to quickly set an initial contour appropriate to the object in the initial contour auto-configuration process. This method helps in reducing the amount of data using multi-resolution analysis, analyzing medical images, and auto-configuring the initial contour appropriate to the object's form.

This paper also proposes the calibration method of using volume data for the initial contour. This method helps in avoiding data loss during multi-resolution analysis and in improving the quality of initial contour. To evaluate the performance of MLevel-set method proposed in this paper, lung segmentation of chest CT images were carried out. The experimental results of the proposed method confirmed that this method helped in generating the initial contour appropriate to the form of lung and improving performance time and the segmentation results.

2 Related studies

2.1 Large-scale medical image management

Hospitals manage enormous amounts of information for diagnosis and treatment of patients. This information is obtained and used for patients in varied places. Evidently, management of information is essential in hospitals. Picture Archiving and Communication System (PACS) and Electronic Medical Record (EMR), which are used in hospitals, make it easy to save and load the information of a patient.

As shown in Fig. 1, PACS is generally composed of various equipment. It receives medical images from imaging devices such as X-ray, MRI, CT, and US scanners and saves them in the archive. The stored medical images are used for diagnosing and treating patients through a reading workstation [14, 7]. Information generated in the process of diagnosing and treating patients is transmitted again to the archive and stored along with the images [6]. As a result, PACS data consist largely of the following two types of data: the image information data and indexes of the image data files, which are Digital Imaging and Communications in Medicine (DICOM) image information, and DB information data, in which the patient exam information is organized [21]. Because image data vastly outnumber DB information in terms of data quantity,

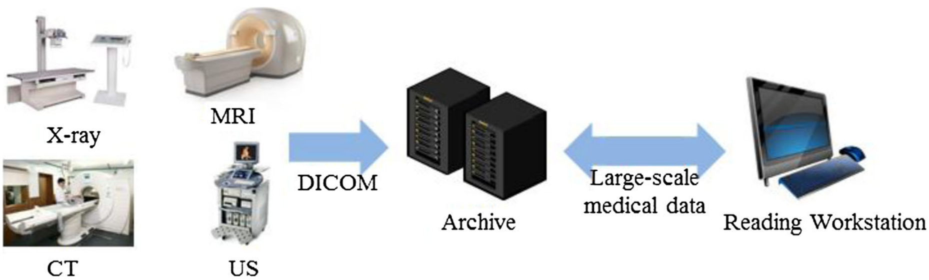


Fig. 1 PACS workflow

they require large-scale data management. A quick and accurate method of transmitting large image data is required, particularly with the increasing variety of reading workstation devices brought about by the development of mobile devices and wireless technology [16, 31, 3].

After the server requests suitable information for the situation from the archive of PACS, the archive of PACS transmits this information to the reading workstation. Besides displaying textual information, the reading workstation shows multimedia information as well. To transmit medical images to the reading workstation rapidly, compression of the medical image is necessary. It should be ensured that the RoI of a medical image does not sustain any damage during compression. One of the main features provided by the JPEG2000, used in DICOM, is RoI coding. It is a technology that first compresses, transmits, and decodes the RoI with better quality than the other regions. In other words, the RoI can be lossless compression in compression processing [26]. Because it transmits the RoI before than the other regions during the image transmission processing, it has the advantage that it can check the RoI rapidly. To use RoI coding in JPEG2000, it is essential to automatically segment the RoI of a medical image accurately.

2.2 Chest CT image

In this study, segmentation was studied using lungs visible in a CT image of the chest. Lungs are organs where early detection is very important because they have no pain-receptor cells. When examining lungs, CT imaging using three-phase imaging is more effective than two-phase imaging chest X-rays. After annual chest CT testing, the American Medical Association announced that the rate of survival with lung cancer increases 20%, in comparison to chest X-rays [4]. Thus, chest CT images are important data when diagnosing for lung diseases. Thus, studies on methods of rapidly and accurately analyzing chest CT images are needed. In chest CT images, each pixel value uses Hounsfield Units (HU); it is expressed as either a negative or a positive value. The HU density is expressed differently depending on the bodily organ, but in the case of chest CT scans, it is composed as shown in Fig. 2 [29]. The number of slices of the CT images differs depending on the physical size of the photographer, but in general, approximately 300~500 chest CT images are generated for each patient.

Although the image sizing of medical images is generated differently depending on the image type, CT images are sized 512×512 pixels or 1,024×1,024 pixels. Furthermore, chest CT images use 12-bit images, not the 8-bit images used in normal images. The visual

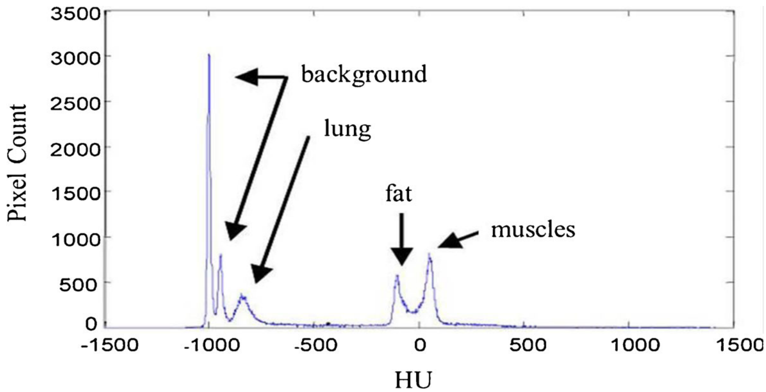


Fig. 2 Histogram of chest CT image

perceptual characteristics of humans perceive a 64 gradation (6 bit) as continuous tonal change. Because medical images cannot be accepted as a 256 gradation (8 bit) because the X-ray strengths that have penetrated the human body differ significantly and need a wider range of the number of gradations, chest CT images are composed of 12 bits, unlike normal images. Therefore, images that express pixels with a 4,096 gradation are used.

2.3 Medical image segmentation methods

In the field of medical image segmentation, many researchers are studying diverse methods of rapidly and accurately segmenting medical images. Segmentation methods using the critical threshold, the most basic methods in image segmentation, such as Watershed, Region-growing, Active Shape Models (ASM), Clustering, and Level-set, are being studied. Recently, research has been conducted on hybrid image segmentation methods that make use of various methods over several stages rather than using just a single method.

The segmentation method using a threshold is the most basic segmentation method in image processing. It is a method of dividing the field by comparing pixel values on the basis of the threshold entered by the user. Figure 3 shows the segmentation of the lung image using −500 HU (*th*) as the threshold value. Methods for automatically establishing thresholds are the repetitive threshold method and the Gaussian distribution method. The repeated threshold method divides the image into two fields with specific threshold values. Each divided area is repeatedly segmented by readjusting the threshold until it becomes indivisible by a particular condition. Even though segmentation can be performed in this manner through simple repetition, it is impossible to obtain an accurate or detailed threshold value. The Gaussian distribution method assumes a Gaussian distribution and automatically calculates an approximate threshold value; however, its problem is that it has limited fields in which it can be effectively utilized. However, because the threshold method is the simplest method with the highest speed of segmentation, it is used widely as an auxiliary segmentation method in other segmentation methods. Image segmentation that makes use of Watershed is a segmentation method that makes use of watershed's possibility to be viewed as a geomorphic surface on which height and depth are expressed by the pixel values. It defines the smallest pixel value as the minimum value through a comparison with the surrounding pixel values in a defined region, and it can segment fields by rising around the minimum point in a manner similar to that of water when it fills up to the lowest point first when rising [28]. Image segmentation with Watershed deteriorates the performance during detailed segmentation. Image segmentation using Region-growing performs segmentation by expanding regions by calculating the level of similarity between adjacent pixel values. It determines whether it belongs to a Seed region by calculating the level of similarity of the adjacent pixel values on the basis of a user designated Seed region [2, 32]. In other words, if the difference between two pixel values is within an absolute threshold value, it expands as the same field, and if it is greater than the

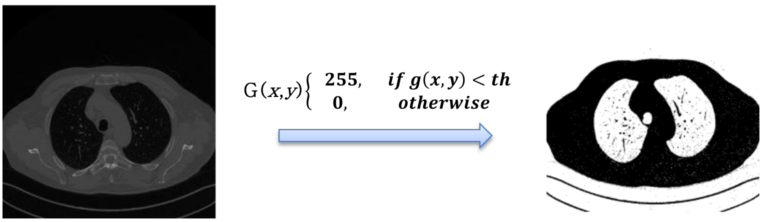


Fig. 3 Segmentation result of chest CT image using threshold method

threshold, it performs the segmentation when halting the expansion. This method is ineffective when there are significant changes to brightness or the boundaries are unclear. Image segmentation using ASM first performs a study using the data and then image segmentation based on the resulting data. This method consists of shape calibration and shape learning processes. Because these have the capacity to restore the image based on the training data even if the boundaries of the segmented image are unclear or lost, it performs excellently in medical image segmentation. As the segmentation performance of this method is influenced by the quality of the learning data, ASM requires various forms of learning data and preliminary work by a professional [8, 11]. Clustering is used in image segmentation for a similar pattern aggregation process that uses the similarity or proximity between pattern groups when a limited number of patterns are clustered in a pattern space to form a set [24]. Segmentation errors arise in clustering when the centrifuge of the cluster is incorrectly calculated or a wrong number of clusters are chosen, and because of its computation complexity as it repeats calculation until the functions converge. Image segmentation using Level-set can overcome the influence from abnormal characteristics such as static, and because it can easily be extended to a random region, it allows segmentation of three-dimensional volumetric data and two-dimensional cross-sectional data. In Level-set, the user must input the initial contour, and in the event that he/she sets an initial contour that is not suitable for the object, the performance is affected. Further, it has a slow processing speed [30].

Although various medical image segmentation methods such as the ones mentioned above are being studied, all of them have certain drawbacks such as slow processing speed or the fact that they necessitate additional input or work by the user. To resolve these problems, research on segmentation of medical images that are automatically implemented without a user input process and with improved performance speed for performing image segmentation is required.

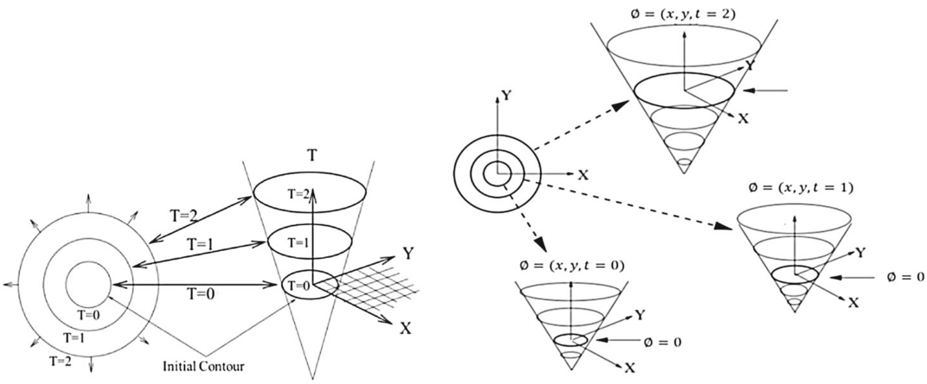
2.4 Image segmentation using Level-set

Level-set is a form of Active Contour Models (ACM). It helps in segmenting images based on the curvature of the initial contour and the images configured over a period of time. It can be formulated by performing mathematical calculations on the contour and the surface. A Level-set does not take the parameters for objects into account. As it is robust to forms and geometric changes, it is suitable to use Level-set in the field of fluid dynamics. Level-set can help in recovering images from irregular characteristics such as noise. In a Level-set, it is also possible to include topological changes independent of locations and forms of the initial contour. Due to these reasons, Level-set is actively applied in the field of image segmentation for extracting, recognizing and identifying a specific object in the medical images [19]. The basic concept of Level-set is that the initial contour keeps moving at a constant rate in a normal direction at a certain point of time. In the Level-set, the speed function F of the initial contour moving in a normal direction is calculated as follows:

$$F = F(L, G, I) \tag{1}$$

Where L is the curvature speed determined by local geometric information such as the normal direction, and G is a wide range of speed determined by shape and location of the contour. I denotes the speed that can apply force independently regardless of shape of the contour. Level-set considers all three speeds and utilizes them variously in each application fields.

Figure 4a shows the extension of the contour from the initial contour according to time T; it also shows the coordinates x and y with change in time [23]. Figure 4b shows the results of



(a) Change in curvature over time (b) Changed Level-set function of ø

Fig. 4 Change in the contour of Level-set

expressing three-dimensional scalar variables ø(*x*, *y*, *t*) as two-dimensional location time functions in order to express the change in the contour with Level-set. The shape progressed at a random time *t* is expressed as a function ø=0 and the distance from the random points (*x*, *y*) to the curve is denoted by *d*, and as shown in the following equation, random points can be expressed as Level-set function ø.

$$\phi(x, y, t) = \pm d, \quad (x, y) \in R^N \tag{2}$$

In other words, ø value for the points on the curve is 0, and ø values for other points in the space are represented as either a negative value or a positive value de-pending on whether the point is inside or outside the curve, and the boundary of the curve is represented as 0. In the Level-set, the contour is developed by speed function *F*. Various speed functions including mean-variance based method and DRSLE-based method are proposed and studied in [17, 5]. Until recently, studies to enhance the performance by improving the speed function of Level-set have been actively underway. The Level-set method is used for lung and brain segmentation as well as for abnormal tissue segmentation in medical images, but the problem faced due to auto-configuration of the initial contour of Level-set that affects its performance has received relatively less attention. Recent studies have shown that segmentation performance can be improved by performing ASM region segmentation or using entropy to set the initial contour of Level-set prior to performing the Level-set method [15].

3 Proposed MLevel-set lung segmentation method using auto-configuration of the initial contour

Level-set is actively applied in the process of image segmentation for extracting, recognizing and expressing specific object from medical images. However, the drawbacks of a Level-set include manual input of initial contour by the user and slow performance speed. This paper proposes the MLevel-set for an auto-configuration of the initial contour as shown in Fig. 5. This MLevel-set helps in improving user input and in increasing performance speeds. It also complements the existing method that requires a user to input the initial contour.

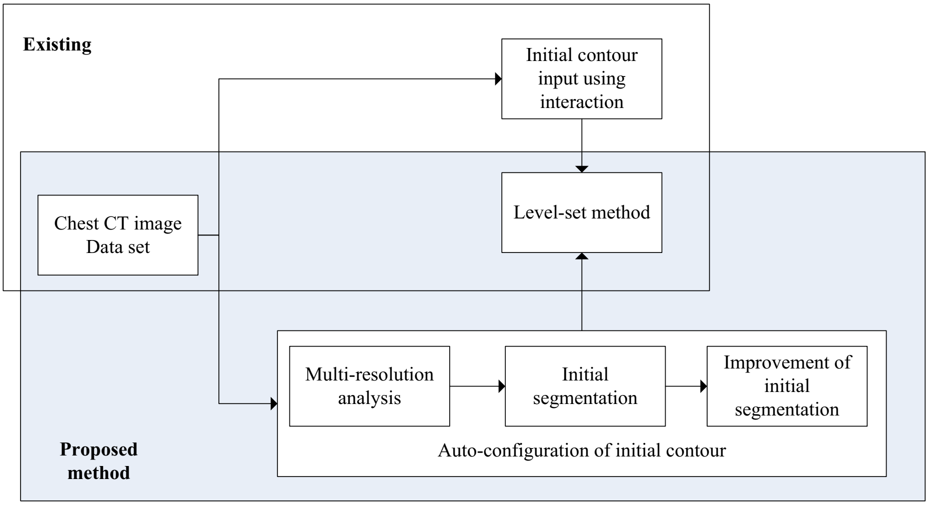


Fig. 5 Image segmentation using MLevel-set

Auto-configuration of the initial contour consists of the following steps: Multi-resolution analysis, Initial segmentation, and Improvement of the initial segmentation.

3.1 Multi-resolution analysis

A multi-resolution analysis is a method of separating signals or images into components having high and low frequencies. This is accomplished by changing the resolution of the signal or the image and by analyzing the characteristics of frequencies appearing on these resolutions. Multi-resolution analysis can be used for data compression. In this technique, the characteristics of a signal or an image remain constant even when the resolution is altered. Thus, the high frequency and low frequency components of each resolution can be easily separated and viewed. Thus, multi-resolution analysis has been used in various fields for characteristic analysis of signals or images. Multi-resolution analysis can used to change the size of an image by reducing its resolution to the desired rate. This implies that multiple blocks of an image can be expressed as one pixel and its resolution can be increased step by step. At the end of this process, one pixel represents one block. Figure 6 shows the levels of multi-resolution analysis images changed in the order of N, N-1, N-2, and N-3 in the shape of a pyramid. As the level of the image changes, the resolutions of the images are reduced by $1/2\times1/2$ each to $y\times x$, $y/2\times x/2$, $y/4\times x/4$, and $y/8\times x/8$ [12].

The present study used image data with different resolutions obtained through a multi-resolution analysis. While processing images, searches are generally carried out for all pixel values in order to analyze the image data. As a result, an $M\times N$ calculation is required when processing $M\times N$ images. When changing the resolution of $M\times N$ images to $M/2\times N/2$, the calculated amount is reduced to $(M\times N)/4$. In this paper, Wavelet transform is used to apply multi-resolution analysis to images.

3.2 Initial segmentation

The initial segmentation process involves selecting the initial region to enable the auto-configuration of an appropriate initial contour. The initial segmentation process consists of

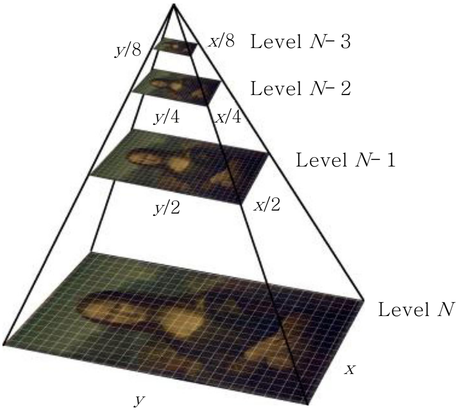


Fig. 6 Structure of multi-resolution analysis

human body detection. This process helps in detecting the body region except the background area and the initial lung area. The body area encompasses the largest area in the chest CT images and is present in the outermost region. After de-creasing the amount of data using the level *N*-2 step of the multi-resolution analysis, the body area can be detected by performing Level-set with the initial contour as shown in Fig. 7. This Level-set has slow performance speed but it can detect the human body area faster since the amount of image data has been reduced.

After detecting the body area, the next step involves extraction of the candidates for lung region. This process helps in generating the initial contour appropriate to suit the lung form. Due to the existence of other organs in its proximity, the lung's form has complex structure when compared to that of a human body Therefore, the information on the lung complexity and the organs around it can't be expressed exactly in the *N*-2 level images. Therefore, the candidate of the lung region is extracted at *N*-1 level, which has higher resolution than in the *N*-2 level. The threshold value is used to extract the candidate lung region. In other words, the density of the lung regions in most images is less than −500 HU. So the lung region can be approximately classified using −500 HU.

Fig. 7 Level-set segmentation for body detection (*red line*: Initial contour)

The data on body area obtained from the histogram distribution and the body detection process helps in extracting the lung region from the background. However, it is not possible to perform an accurate segmentation process. This is due to the fact that the optimal threshold values in segmentation using histogram vary from one image to the other. In such instances, the segmented region includes the lung region, bronchi and blood vessels. To extract the exact lung region, all regions except the lung tissues should be removed.

The lung region consists of various tissues including lung tissues, air and pulmonary vessels. The bronchi included in the candidate's lung regions are composed only of air as they serve as a passage for air circulation. The interior region of a lung consists of various tissues. And, its exterior region is made of simple tissues or materials. The histogram distribution of the lung's exterior region is thus different from that of its interior region. The graphs shown in Fig. 8 represent the distribution of variance and areas of the lung region and other regions respectively. Selection of the final lung region includes:

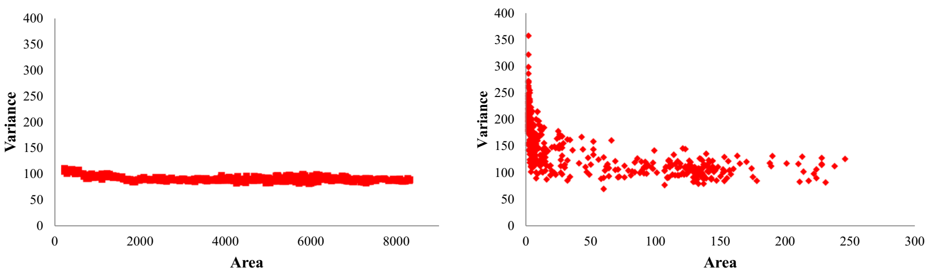
- Selecting of the lung region using a histogram distribution process.
- Completing the initial segmentation.

3.3 Improvement of initial segmentation

The improvement of initial segmentation process of initial segmentation is the last step in the auto-configuration process. It is performed to remove errors of auto-configured initial contour and to reconstruct the damaged region. As multi-resolution analysis leads to data loss, it is imperative to undertake the improvement of initial segmentation process for the region under study. However, there is no loss of data in the lung region present in the beginning and end of the lung as well as in the small region present away from the large region of the specific slice as shown in Fig. 9.

A small lung region presents an insufficient data making it difficult to segment the lung region using multi-resolution analysis. This initial segmentation is used as an initial contour of Level-set that will be carried out in the original image. Therefore, an improper initial segmentation of the small lung regions leads to problem in the performance of the entire lung segmentation process.

The chest image bundles found in the axial plane encompass data set of chest CT images as shown in Fig. 10a. These images help in generating the volume data. Also, forms of the lung



(a) Lung region (b) Other regions

Fig. 8 Distribution of variance and area

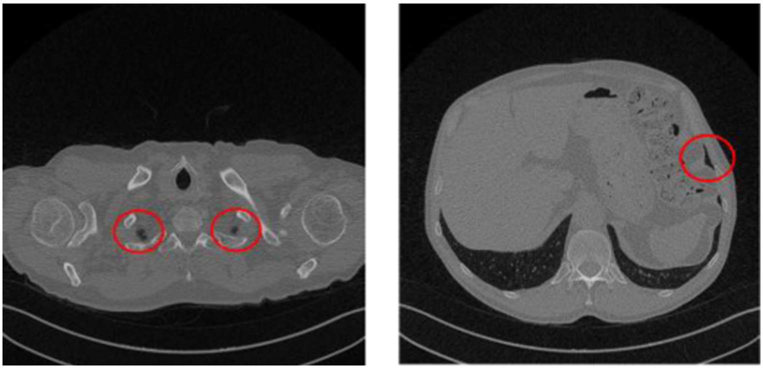
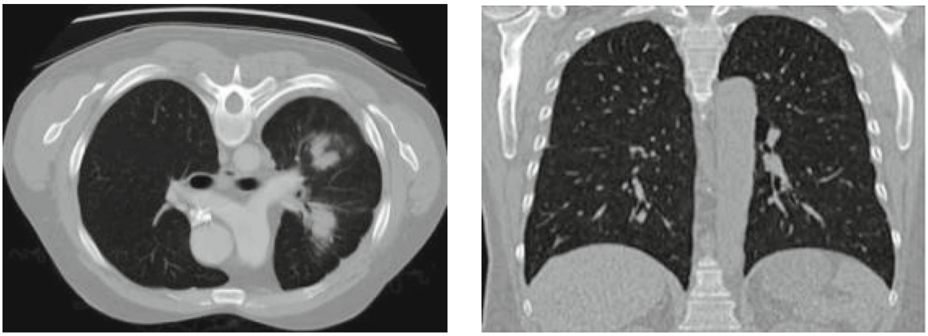


Fig. 9 Small sections in a chest CT images

between successive slices are similar in nature and are connected naturally as shown in Fig. 10b. So, the volume data of chest CT images can be used to predict and improve the insufficient data. The connection of coronal plane of the lung has no complex form, so the next slice information can be predicted by applying the linear equation. From the segmentation results, select the n and $n+1$ as a reference slice. Next, devise the linear equation using coordinates of the boundary points on the two reference segmentation results. With the help of the linear equation using two reference segmentation images, the segmentation boundary coordinates of the $n+2$ slice can be predicted. By comparing these predicted results with boundary coordinates of the initial segmentation, the segmentation results with error can be reconstructed. In the improvement of initial segmentation process, the lung region will be restored using volume data of chest CT images and the linear equation. When the improvement of initial segmentation process is expressed in formula, it will be as follows:

$$\begin{aligned} P_{n+2} &= L(m_n, m_{n+1}) \\ M_L &= P_{n+2} + m_{n+2} \\ I_{n+2} &= M_L \cap T_{n+2} \end{aligned} \tag{3}$$

After defining the linear equation using reference images of m_n and m_{n+1}, the next step is to generate the predicted segmentation results, P_{n+2}. Then, by combining P_{n+2} and m_{n+2}, which



(a) Axial chest CT image

(b) Coronal chest CT image

Fig. 10 Chest CT dataset

are the initial segmentation results, the adjusted result M_L can be calculated. While generating M_L, an error generated due to the absence of the lung region can occur. Generation of I_{n+2} is the next step in this process. This is done by combining the threshold value segmentation region, T_{n+2}, and by excluding the non-lung region. Finally, the generated I_{n+2} is selected as an initial contour of the Level-set for the lung segmentation.

The initial contour is the segmentation information obtained from initial segmentation of the lung. This information does not provide accurate results for extracting the lung region. A multi-resolution analysis is performed on the initial contour to reduce the performance time of the initial segmentation process. It is thus mandatory to undertake the improvement of initial segmentation process to restore the size of the initial contour. This implies that after completing the auto-configuration of the initial contour, the initial contour information is reconstructed to its original data, and is then used as the initial contour of Level-set. The initial contour uses the initial segmentation results for auto-configuring purposes. Hence, the lung region is segmented with approximate results. However, owing to its similarity in location and form, the initial contour of the chest CT images can be used on the Level-set to perform the final lung segmentation.

4 Experimental results

To experiment the method proposed in this paper, DB of VESSEL Segmentation in the Lung 2012 (VESSEL12) was used. VESSEL12 DB includes the chest CT image dataset and the segmentation mask dataset, which is the lung region segmentation information. The Level-set used in the experiment uses the DRLES speed function proposed by *Li* and using Dice's Overlap to measure the lung region segmentation performance, accuracy (S) and standard deviation (Std) were measured [18, 10, 27].

Figure 11 shows the segmented lung region using the proposed method. And Table 1 shows the experiment results of the proposed method. To compare the performance, the Level-set using the initial contour generated through the user input was performed additionally. The initial contour input time by the user was 10 to 20 s. And, the input time depended on the forms and sizes of the lung. Additionally, performance was compared after segmenting the lungs using the Region-growing and watershed methods. The user established seeds for each slice in order to input Region-growing seeds.

Fig. 11 MLevel-set lung segmentation results using auto-configuration of the initial contour

Table 1 Lung segmentation experiment results

	Region-growing	Watershed	User input initial contour	Proposed MLevel-set
S	0.975	0.968	0.957	0.984
Std	0.140	0.174	0.128	0.170

User input Level-set, Region-growing, Watershed, and the proposed method have accuracy rate of more than 0.95. And, the proposed method had higher accuracy than the user input method. The standard deviation of accuracy help to constantly maintain the performance of the user input Level-set in each slice. And, when compared to the proposed method, the image segmentation method of the user input Level-set had constant performance for each slice. Unlike the proposed auto-configuration method, other segmentation methods intervene in user's input for image segmentation process. This leads to higher performance in the standard deviation. The initial contour set by the user's naked eye was less optimized and slow when compared with the MLevel-set. This resulted in lower performance of the user input Level-set. The region outside the lung exists in a non-optimized region. It thus showed lower performance than that of a MLevel-set. In addition, as shown in Table 2, the necessary number of cycles for the user input and proposed method was measured as 5.373×10^{11} and 8.569×10^{9}, respectively. Cycles that are expended when the user inputs initial contours were excluded from the user input level-set. This shows that the performance of Level-set was reduced in the proposed method because a more suitable initial contour was entered in this method. It is possible to confirm with this comparison whether the level-set performance speed can be improved through automatic input of initial contours.

5 Conclusions

Owing to the improvements in the performance of medical imaging equipment, medical diagnosis using image analysis with computer has become significant. Furthermore, the resolution, number, and volume of medical images have increased. Large-scale medical image management is important for specialists for easily using medical images in diagnosis and treatment. Image compression is required for efficient transmission and storage of large medical image data. Although DICOM's JPEG 2000 RoI Coding compresses RoI without damaging it, the method for segmenting RoI is not specified. As a result, image segmentation is required for managing large volumes of medical image data.

The medical image segmentation should be performed first before undertaking other steps in of medical image processing. However, the similarities in the biological characteristics of organs cause difficulties in performing region segmentation of medical images. Of all the medical image segmentation methods, Level-set has a slow performance speed as it requires the user to configure an initial contour. However, the performance speed can be improved by entering appropriate initial contour to the form of the object. This paper proposed a MLevel-set that proposed auto-configuration of the initial contour to as a solution to this problem. In this

Table 2 Number of cycles needed in segmentation of lung regions

Method	Cycle
User input initial contour	5.373×10^{11}
Proposed MLevel-set	8.569×10^{9}

MLevel-set, multi-resolution analysis was applied to reduce the computation of auto-configuration process of the initial contour. And, to rectify errors present in the initial contour caused by data loss. To rectify these errors, the volume data characteristics of chest CT images and segmentation reconstruction method using linear equations are proposed in this paper. According to the experimental results, it was confirmed that the proposed method had lower performance and higher accuracy when compared to the Level-set using the initial contour through the user input, but overall, it was established that the proposed method had higher segmentation accuracy.

In the future, studies on the detailed segmentation for the bronchi, pulmonary vessels, and lobe, which exist within the segmented lung region and on automatic detection of a suspicious region will be carried out.

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