# Abstract

Medical image segmentation is one of the most essential steps for many medical diagnoses. Medical image segmentation has particular obstacles comparing with natural image segmentation, such as, accuracy and intensity non-uniformity of medical images. Although numerous approaches have been suggested to tackle the problem by combining spatial priors and appearance priors, most of previous methods suffer from laborious preprocessing or the limitation of application range. This thesis proposes the registration guided medical image segmentation method using Random forests classification method to alleviate the preprocessing and to generate accurate results. The proposed method utilizes spatial information by the proposed registration guide and appearance information using Random forests. The registration guide searches the nearest images of a test image from a training set and transfer their labels to the test image by using a deformable registration method. The deformed labels of nearest images are used as spatial priors of a target organ. Discrete Markov random field energy formulation fuses the spatial priors and the appearance priors to generate the accurate

result. Qualitative and quantitative analysis demonstrates the accuracy and robustness of the proposed method.

**keywords:** Medical Image, Segmentation, Random Forest, Registration Guide, X-ray, Deformable Registration

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# Chapter 1

# Introduction

Medical image segmentation is one of the most essential steps for the diagnoses based on the medical images, such as, detecting tumors in organs, measuring the volume of organs, and etc.. Despite of the importance of the segmentation task, it has not been thoroughly solved yet due to the challenges, such as, high dimensionality, high noise, intensity non-uniformity, and desired high accuracy [1].

Numerous approaches have been suggested to overcome the challenges by using prior information of the medical images [2]. The prior information of the medical images can be obtained by learning from the training samples which have similar information of a target image. The prior information is useful to compensate the high noise and intensity non-uniformity of medical images, since target organs are usually positioned at the predictable positions and have consistent shapes by the nature of medical images.

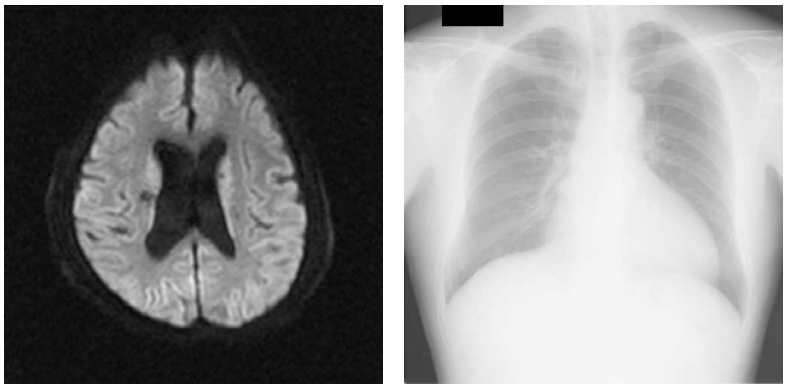
Many previous works have focused on the global prior information,

such as, global shape priors, intensity range, and position. The global prior information is usually deprecated to gain robustness against outliers and reduce the running time and memory usage. However, the deprecated global information does not reflect the detailed information of target objects, and it hinders the methods achieving high accuracy. The shapes and the intensity distributions of target objects can vary due to the damages or intensity non-uniformity even though the objects are in the same class.

Figure 1.1 (a) displays the axial plane of the diffusion weighted image (DWI) of a post cardiac arrest patient. The resolution of medical images is typically lower than natural photographic images because high radiation exposure to patients, which may harm patients, is required to capture clear images. Figure 1.1 (b) shows a lung x-ray image. Although required radiation for x-ray is lower than other medical images, the boundary of lung is vague and not unique.

In this thesis, the registration guided medical image segmentation method is proposed to overcome the limitation of global priors. At the training stage, the proposed method learns the global appearance information using Random Forest [3]. The features, which contain information of gradient and intensity, are extracted to represent the appearance information. At the test stage, the method search the nearest images using local detection and simple registration method to obtain spatial priors. The spatial prior reflects more detailed information of target objects better than the global spatial priors. The spatial prior and the global appearance prior are combined into the

Markov Random Field(MRF) [4] energy formulation for segmentation.



(a) The sample of diffusion weighted image of the post-cardiac arrest patient

(b) The sample of a lung x-ray image

Figure 1.1: Examples of the medical images

# Chapter 2

# Related Works

The early approaches using intensity and gradient, such as, region growing method [5] and watershed method [6] do not present accurate results since they do not use high level information, such as, shape prior, or position information. The methods only assume that the target organs have the specific range of intensity distribution. Thus, the methods are only capable of capturing the approximated region of the target objects because of the intensity non-uniformity of the medical images.

The explicit shape-prior based methods, such as active shape model(ASM)[7], and active appearance model(AAM) [8], have presented impressive results on many applications [9, 10, 11] by using learned prior information, however, the methods have a few limitations. The methods require complicated preprocessing steps, such as, landmark point matching at the training stage. The complicated preprocessing steps hinder the methods to be applied to wide range of applications and, sometimes, even decrease the accuracy of

the methods since the errors which occurred at the preprocessing steps usually propagate to the test stage of the methods. Also, the explicit shape-prior based methods generally use the global shape prior information or its variations. Thus, the results of the methods are not accurate enough when the target organs or objects have complicated or inconsistent shapes.

The Level-set based methods [12, 13] have been applied to wide range of applications. Although numerous variations of the method have been suggested, the level-set methods implicitly assume that the gradient magnitude at the boundary of target organs is higher than the inside or outside of the target organs. Thus, the methods are susceptible to organs with high intensity variance and low boundary gradient.

Recently, machine learning based methods [14, 15, 16] have been highlighted because of its explicit usages of high-level information, less complicated preprocessing, and high accuracy. Among various machine learning algorithms, random forest [3] has been widely used because of its efficiency on large data bases and its anti-overfitting property. The random forest and its extension based methods have shown impressive results by only using the classification results, when the target organs have small deformity.

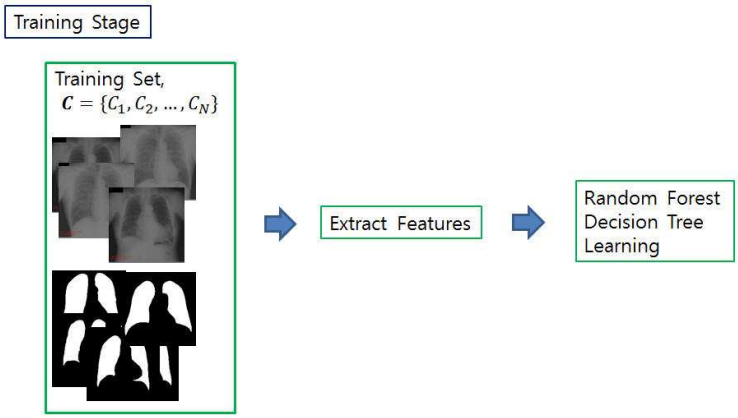
However, previous machine learning based methods do not explicitly consider the spatial information, such as shape priors or position priors. Monno et al. suggested the segmentation method based on the random forest classification [17]. They only consider the appearance of hippocampus, thus the method requires preprocessing step to catch the position of hip-

pocampus. Also, Lempitsky et al. suggested the delineation method based on the random forest [16]. They implicitly consider the spatial information by including the spatial coordinates in their feature selection. The spatial information is only used as global priors, thus, the influence of spatial information is not distinctive.

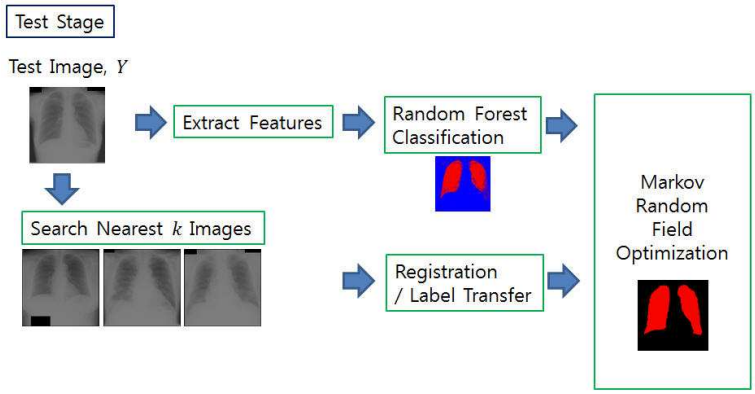
# Chapter 3

# Algorithm Overview

The proposed algorithm is largely divided by a training stage and a test stage. Figure 3.1 demonstrates the overview of the proposed method. The proposed method learns the appearance information by learning labeled images with intensity and gradient features at the training stage. Each pixel in the labeled training images are trained to avoid the overfitting problem which can occur when the number of training sample is small. After learning the appearance information, the proposed method generate the probability map of an input image by Random forests classification method. The probability map roughly estimates the label of a target organ without any prior information. The registration guide reflects the shape prior information of a target organ to generate more accurate results. The shape information from the registration guide and the appearance information from the probability map are combined in an Markov random field energy formulation. By optimizing the segmentation energy function by a discrete optimization method,




(a) The training stage of the proposed algorithm




(b) The test stage of the proposed algorithm

Figure 3.1: The overview of the proposed algorithm. The proposed method learns the appearance information by Random forests at the test stage. The trained information is used to generate the probability map at the test stage. The registration guide reflects the shape information of a target object.

the proposed method generates a final result, which is a binary label.

# Chapter 4

# Random Forest Classification

## 4.1 Feature Extraction

Features are extracted from each pixel of an image $I$. Each feature $f$ represents the appearance of a pixel and its coordinate. To represent the appearance of a pixel and its adjacent pixels, a feature includes neighborhood intensity map $A$, histogram of oriented gradients(HOG) $G$.

$$f_i = [A, G, x] \tag{4.1}$$

The neighborhood intensity map $A$ contains the intensity value of a pixel at x and its adjacent pixels. The neighborhood of the pixel is defined as nearby pixels which are connected with the pixel by 8-connectivity for two dimensional images. The neighborhood intensity map improves the separability of features which is not represented enough with the single in-

tensity value of a pixel. The size of the neighborhood intensity map has a trade-off relationship of the separability and the feature dimension. If the size of the neighborhood intensity map is large, the separability of the feature becomes high while the feature dimension increases. The size of the neighborhood intensity map is set to take care of only directly connected neighborhood in the 8-connectivity neighborhood system to have the appropriate separability and the feature dimension. HOG feature is widely used in the computer vision field and the medical imaging field for describing the edge information. HOG feature in the feature $f$ describe the gradient information of adjacent pixels. For HOG feature $G$, all pixels in the predefined window are considered since the number of pixels in the window does not increase the dimension of features.

## 4.2 Random Forests

Random forest classification method is adopted to estimate the probability of features whether they belong to foreground labels or background labels. The estimation is basically binary decision for the segmentation problem. Thus, in this chapter, the random forest method is explained in the binary classification aspect. Random forest trains the set of labeled features to generate a randomized tree to guess the label of input features.

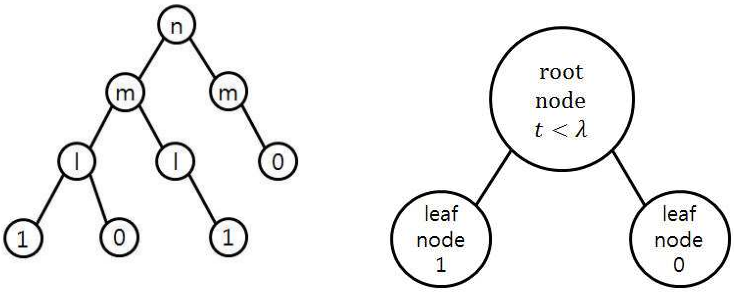
$$t_p = \sum_{r \in \gamma} w_r \cdot f_r \tag{4.2}$$

The randomized tree is constructed by the 'voting' nodes which determines the each feature belonging to a foreground class or background class. The voting nodes is two-leaf-one-root tree for the binary classification, which the decision of binary tree is determined by the node function $t_p$ which is described by the Eq 6.1.

Figure 4.1(a) presents an example of a binary decision tree. A binary decision tree is consisted of nodes with two leaves. Two leaves represent the decision of the node function at the node as shown in Figure 4.1(b).

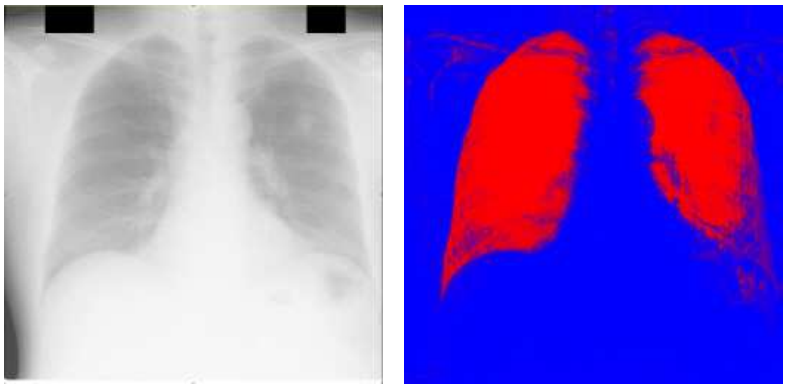
$r$ and $w_r$ represents the index of feature elements and the random weights of feature elements, respectively. The Random forest constructs multiple randomized trees which is consisted of the voting nodes from the partial set of features. The rest of unassigned features for each randomized tree are used to measure the out-of-bag error to determine the best tree. The out-of-bag error is calculated by testing the unassigned features for each tree. The tree with the smallest out-of-bag error is decided to be the trained tree and used as a classifier for the testing features.

The probability $p_{rf}$ represents the foreground probability of features which is derived from Random forest method. $p_{rf}$ is calculated as the proportion of decision tress that classified a feature to the foreground label. The proportion of decision trees is obtained by the average voting method[]. The method averages the un-weighted class votes where each member vote for the foreground label. Figure 4.2 displays the input X-ray image and its random forest probability map. As shown in Figure 4.2(b), random for-




(a) A binary decision tree (b) A voting node and its function

Figure 4.1: An example of a binary decision tree and a voting node.



(a) Input image (b) Random forest probability map

Figure 4.2: Input X-Ray lung image and its random forest classification probability

est probability result roughly estimates the foreground label with outliers outside the target lung area.

# Chapter 5

# Registration Guide

In this section, the registration guide for spatial prior information is introduced. When the input image is given, the proposed method searches nearest $k$ images by matching intensity distribution inside the given training label. After $k$ nearest images are determined, the deformable registration method is applied for the label transfer to produce spatial priors. The registration guide helps the segmentation of target organs by catching local variance of positions of the target objet.

## 5.1 Nearest Image Search

Nearest $k$ images are selected from the training set $\mathbf{C} = [C_1, C_2, \ldots, C_N]$ by intensity distribution matching. Under the assumption that a target object is located at the similar positions of the labeled objects of the training samples, the intensity distribution matching between each training sample $C_i$ and the

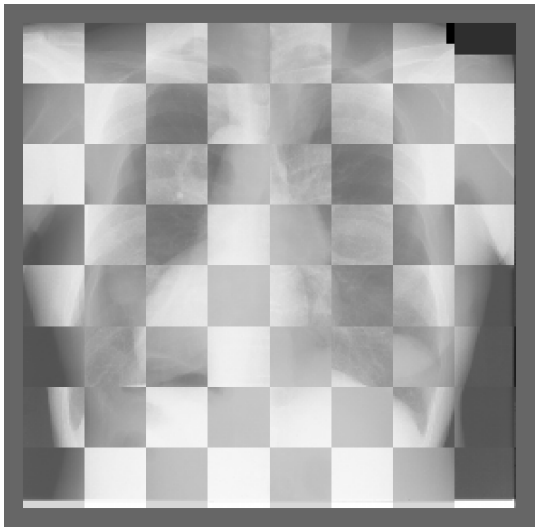
input image is only conducted for inside the label of training samples as following,

$$C^* = \min_{C_i} \sum_{l \in L_i} \| I_{C_i \circ T_i(l)} - I_Y \|. \tag{5.1}$$

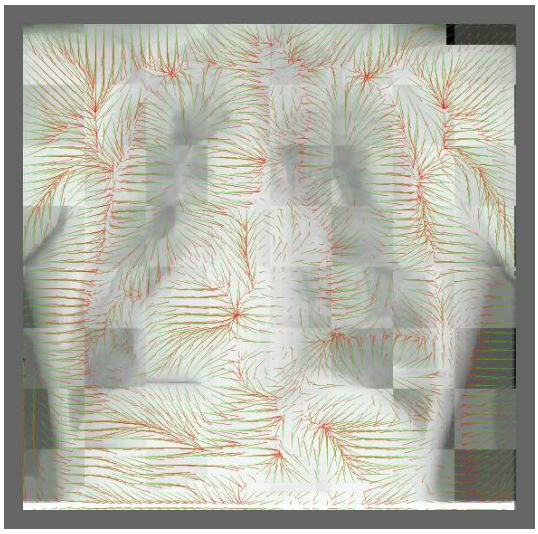
The proposed searching algorithm generates moderate results efficiently under the assumption that the target objects have consistent positions. The proposed method does not require very accurate results of nearest images since the nearest images are deformed by the registration method.

## 5.2 Label Transfer

Since the label $L_i$ of the nearest image $C_i$ does not accurately represents the shape and the position of the input image $Y$, a deformable registration method is applied to transfer $L_i$ to $Y$. DROP [] is one of the most widely used deformable registration algorithm because of its efficiency and ease of use. DROP treats the deformable registration problem as a discrete Markov Random Field(MRF) energy optimization problem. Deformation field values are quantized into the labels of MRF. Figure Numerous energy functions, such as, sum of absolute differences, mutual information, truncated quadratic function, and etc., are possible to be adapted in the DROP framework. In this paper, the sum of absolute difference energy function is used since it shows the best results for the label transfer, experimentally. Figure 5.1 displays the image registration result by DROP. The image difference



(a) Unregistered input image and the nearest image.



(b) Registered input image and the nearest image. Arrows indicate the deformation flows. Red to green gradation displays the source position and its deformed position.

Figure 5.1: Registration example between an input image and the nearest image.

between the input image and the nearest image is moderately decreased.

## 5.3 Energy Formulation

The spatial prior probability $g_x$ is obtained from the deformed nearest $k$ images. Where $\mathbf{C}' = [C_1^*, C_2^*, ..., C_k^*]$ represents the set of deformed nearest images, $g_x$ is calculated as the average of labels at $x$. The spatial energy $E(g_x)$ is by the negative log of $g(x)$.

$$g_x = \sum_{i}^{k} L_i(x)/k, \tag{5.2}$$

$$E(g_x) = -log(g_x). \tag{5.3}$$

The appearance probability $p^r f(x)$ acquired from the random forest classification probability estimation is combined with the spatial energy $E(g(x))$ into the data term of discrete MRF energy function as follows,

$$E(l) = (1-\beta)\sum_{x} \varphi(p_x^{rf}(l), g_x(l)) + \beta \sum_{(p,q)\in\varepsilon} min(S(l_p, l_q), d_s). \tag{5.4}$$

The data term of the Equation 5.5 is defined as the combination of $p^r f_x(l)$ and $g_x(l)$.

$$\varphi(p_x^{rf}(l), g_x(l)) = (1-\alpha)min(-ln(p_x^{rf}(l)), d_1) + \alpha min(E(g_x(l), d_2). \tag{5.5}$$

MRF energy function $E(l)$ is optimized by the Graph cut algorithm since the energy function has a submodular smoothness cost function.

# Chapter 6

# Experimental Results

For the evaluation of the proposed method, the two dimensional X-Ray images from the Japanese Society of Radiological Technology(JSRT) database [18] are used for quantitative and qualitative validations. The database is consisted of 154 nodule lung X-ray images and 93 non-nodule lung X-ray images. 40 random images are selected as the training images and other 40 random images are selected as the test images. The images are re-sampled to 256 by 256 images for the efficient evaluation. The lung masks annotated by experts are provided for training and evaluation. Annangi et al.'s region based level set based method [13] is compared with the proposed method for the quantitative analysis since the level-set based method is the state of the art method for lung segmentation on JSRT X-ray database. Since Annangi et al. do not provide the source code or the executable, qualitative comparison is hard to be made.

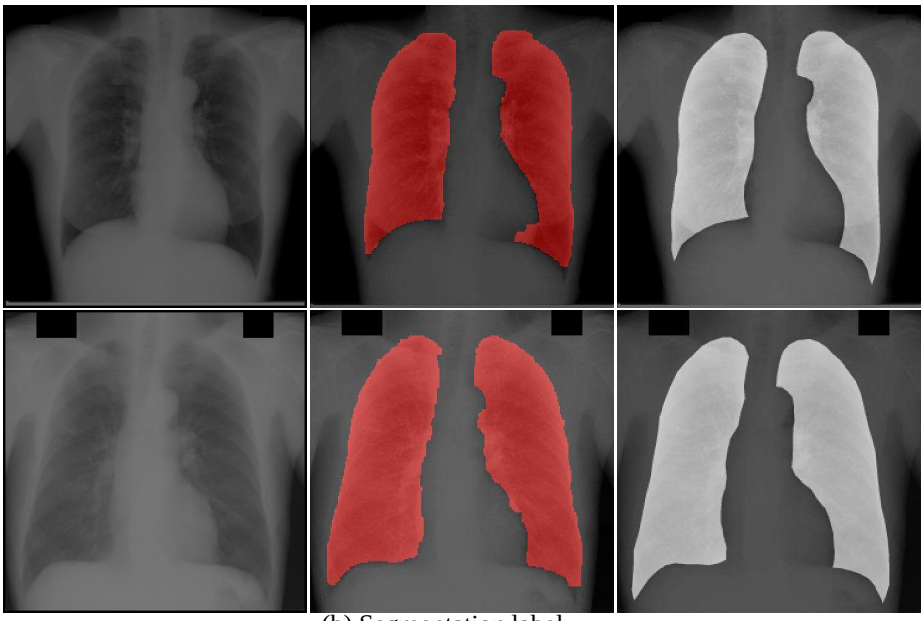
## 6.1 Qualitative Evaluation

In this section, the qualitative evaluation for the lung X-ray images is presented. Figure 6.1 presents the exemplary input images, segmentation results, and the ground truth. The segmentation results are labeled as red. As shown in Figure 6.1 (a), the test images have large variations for intensity distribution, the shapes of lungs, and the size of lungs. The difference was resulted in by different protocols of X-ray machines and inter-patient differences. The proposed method successfully extracted left and right lungs regardless of the variations. Since the proposed method learns the neighborhood intensity maps and the HOG feature of each pixel in the training set, the number of training samples is enough to handle the difference in intensity distribution. Therefore, the proposed method shows robustness to shape and intensity variation of test images.

## 6.2 Quantitative Analysis

The comparison between the proposed method and the region based level based method is measured by the dice's coefficient(DSC). DSC is one of the most widely used metric to measure the accuracy of medical image segmentation. DSC measures the proportion of overlapped region over the sum of both regions of the input label and the ground truth label.

$$DSC = \frac{2|A \bigcap B|}{|A| + |B|}. \tag{6.1}$$



(a) Input Images (b) Segmentation label by the proposed method (c) Ground Truth

Figure 6.1: An example of segmentation result of the proposed method. The proposed method successfully extracts lung from two dimensional X-ray images

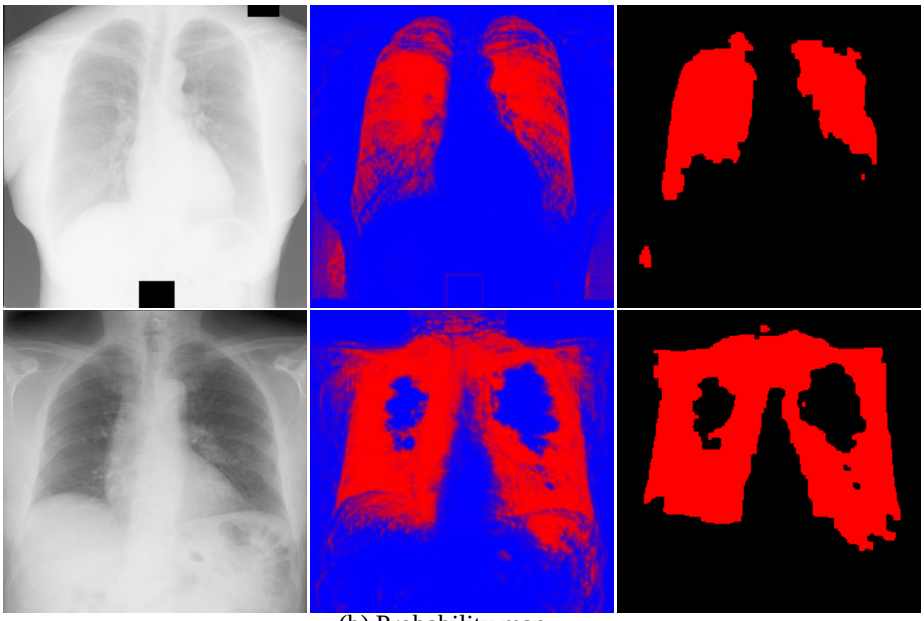
Table 6.1: Quantitative analysis of the proposed method and the region based level set method

| | Proposed | Region based Level Set |
|---|---|---|
| Average DSC | 0.916 | 0.88 |
| Std. DSC | 0.071 | 0.07 |

The proposed method outperforms the region based level set based method on the average DSC by about 0.3, however, the standard deviation of both methods are similar. The standard deviation of the proposed method is increased because of the failure cases, which will be presented in the next section. As mentioned above, since the authors of the region based level set method do not provide any public codes or executables, the average DSC and the standard deviation is referred from their paper [13]. Table 6.2 shows the average DSC and the standard deviation.

## 6.3 Failure Cases

The proposed method failed to extract the lung regions of x-ray images when the input images have singular intensity distribution. Figure 6.2 presents the exemplary input images, probability maps, and results of failure cases. The proposed method does not work properly by two major flaws. First, the proposed method may produce inaccurate results when the registration guide lead the method to false directions. The second row of Figure 6.2 shows an example of the failure case when the registration guide fails to lead the proposed method to an accurate result.



(a) Input Images

(b) Probability map obtained by the Random forest method

(c) Results

Figure 6.2: An example of failure cases of the proposed method.

Second, the proposed method does not work when Random forest method fails to extract seriously damaged probability maps as shown in the first row of Figure 6.2 since the proposed method is heavily based on it. Even though the registration guide amend the contamination of the probability maps, the results of the proposed method shows that seriously damaged probability maps do not lead to accurate result.

# Chapter 7

# Conclusion

This thesis proposes the registration guided medical image segmentation method using random forest classification. The proposed problem utilizes both appearance information and spatial information. The extracted features containing the appearance information of a given image are learned by using random forest method. Also, the registration guided spatial information is combined to the energy formulation to overcome the global spatial priors, which usually have burdensome preprocessing. The proposed method shows excellent results on two dimensional X-ray images comparing with the state of the art method.

However, the proposed method is time-consuming at the training stage. This time-consumption can be reduced by applying small dimensional features. Therefore, searching feasible and efficient features will be one of the future works of this thesis. Also, the accuracy of the proposed method can be deteriorated when the registration guide does not work properly. The

false guide may lead false segmentation results, even though the appearance probability tends to correct the wrong results. The flexible adaptation of the registration guide which determines whether to apply the guide or not based on the reliability of registration can be one solution for the false guidance, and this will also be the remaining work of the proposed method.

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# 초 록

의료 영상 영역화는 의료 영상을 이용한 검진에서 가장 중요한 과정 중의 하나이며, 최근까지 활발한 연구가 진행되고 있는 중이다. 의료 영상 영역화 문제를 해결하기 위해 수많은 사전 정보를 이용하는 방법론들이 제시되었지만, 많은 방법들이 사전 정보를 활용하기 위한 전처리 과정의 복잡성과 활용될 수 있는 영상의 한계를 가지고 있었다. 본 학위 논문에서는 랜덤 포레스트 기법을 이용한 정합 지표 의료 영상 영역화 알고리즘을 제안하여 기존의 방법들이 가지고 있던 문제점인 전처리 과정의 복잡성을 완화하고, 정확한 영역화 결과를 얻어내는 것을 목표로 한다. 제안되는 기법은 모양 사전 정보를 정합 지표를 이용하여 활용하며, 이미지의 외양 정보는 랜덤 포레스트 기법을 이용하여 학습한다. 정합지표는 학습을 위한 훈련 영상들의 집합에서 실험 영상과 가장 가까운 영상을 선택하여, 훈련 영상에서 주어진 영역 정보를 실험 영상으로 형상변이 정합 기법을 통해 전달하여 모양 사전 정보를 얻을 수 있도록 한다. 학습된 외양 정보와 모양 사전 정보는 이산 Markov Random Field 에너지에 포함되어 이산 최적화 기법을 통해 정확한 의료 영상에서의 영역화 결과를 얻도록 한다. 본 논문에서 제시된 양적,

질적 결과는 제시된 기법의 정확도를 보여준다.

**주요어:** 의료 영상, 영역화, 랜덤 포레스트, 정합 지표, X-ray, 형상 변이 정합

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# 감사의 글

학부생 인턴으로 시작하여 신호처리연구실에서 짧다면 짧은 3년 반의 기간이 지나 어느덧 제가 석사를 받고 졸업을 하게 되었습니다. 짧은 석사과정이었지만, 주변의 수많은 도움을 받아서 석사를 무사히 마칠 수 있었기에 석사 논문을 마무리하기에 앞서 감사의 마음을 전하고자 합니다.

우선 부족한 저를 연구실의 일원으로 받아주시고, 석사 기간동안 많은 가르침을 내려주신 이상욱 교수님 감사합니다. 앞으로 어떤 일을 하게 되던지 교수님의 가르침을 가슴 속에 품고 삶의 지표로 삼아 노력하도록 하겠습니다. 또한 제 석사 논문과 연구실에서 수행하였던 프로젝트들에 많은 도움을 주신 윤일동 교수님께 감사드린다는 말을 전하고 싶습니다. 윤일동 교수님의 폭넓은 지식과 다양한 아이디어는 제가 연구를 수행함에 있어서 저의 닫혀 있던 시야를 트이게 하였습니다. 윤일동 교수님이 계셨기에 석사 과정 동안 미약하지만 성과를 낼 수 있었습니다. 저를 처음 인턴으로 뽑아서 가르쳐주신 심학준 교수님 감사드립니다. 기본도 모르는 저를 처음부터 차근차근 가르쳐주시고, 경험을 쌓게 해주셔서 저의 석사 연구가 좀 더 수월할 수 있었습니다.

그리고 저의 석사 논문을 심사해주신 이경무 교수님께도 감사드립니다. 바쁘신 가운데 귀중한 시간을 내어주셔서 졸업을 무사히 할 수 있었던 것 같습니다. 평소 비젼세미나와 수업 때 연구에 관한 많은 것을 알려주셔서 저의 연구에 큰 도움이 되었습니다.

대학원 생활동안 함께 지내며 많은 것을 함께한 대학원 선후배님들에게도 감사의 말씀을 전합니다. 부족한 제가 좋은 연구실에 들어오는 행운을 가지게 되어 많은 도움을 받았던 것 같습니다. 3년동안 함께하는 동안 많은 추억을 함께할 수 있어서 행복할 수 있었습니다. 너무 많은 추억이 있는지라 하나하나 열거할 순 없지만, 모두 소중한 기억들로 남아있을 것입니다. 앞으로 하는 모든 일들과 연구에 행운이 깃들기를 바랍니다.

또한 항상 저를 돌보아주시고 제가 하는 모든 일에 응원을 해주신 가족들에게 감사드립니다. 특히 부모님의 응원과 사랑이 있었기에 지금까지 많은 일을 헤쳐나갈 수 있었습니다. 아주 작은 결과이지만, 조금이나마 부모님의 노력의 결실로 보여질 수 있기를 바랍니다. 늘 한결같이 공부하시고 배우시려는 삶에 대한 지혜와 자세로 저에게 귀감이 되시는 외할아버지, 외할머니께도 감사드립니다. 앞으로 더욱 노력하여 큰 은혜에 보답할 수 있도록 노력하겠습니다.