Automated Liver Segmentation Using Multislice CT Images

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SUMMARY

With practical applications of multislice CT, high-speed imaging has drastically become possible in recent years as compared with the past and imaging the liver twice during the time a patient holds his breath once has become possible in liver CT imaging using contrast media. Thus, three-dimensional images of two time phases differing in the circulatory state of a contrast medium are obtainable without positional discrepancies. The authors propose an automated liver area extracting (segmenting) method using three-dimensional CT images of two time phases of a contrast medium for extracting the shape of the liver. This method first constructs a two-dimensional characteristic (feature) space having the CT values of time phases on each axis from the three-dimensional images of a two time phase portion imaged immediately after and 10-plus seconds after the infusion of a contrast medium. The method extracts areas showing changes in the contrast medium corresponding to the liver in this space and generates images with the liver region emphasized using these. The method then determines the liver region by performing opening and closing procedures on the liver area-emphasized images generated. Finally, it determines the liver region by a three-dimensional component connecting procedure using geometric shape characteristics of the blood vessels, tumors, and so on. The efficacy of using images of two time phases simultaneously has been verified by applying the proposed method to nine cases. © 2003 Wiley Periodicals, Inc. Syst Comp Jpn, 34(9): 71–82, 2003; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/scj.10210

Key words: segmentation; contrasted images; time variable images; histogram analyses; morphology.

1. Introduction

With the recent advances in imaging machines such as CT and MR, imaging particularly high-resolution images in less time than in the past has become possible. Thus, the demand for using the three-dimensional images obtained for visualizing, quantifying, and surgical planning purposes has been increasing. However, currently the target organ extraction has been performed by manual tracing by doctors for such purposes, which requires tremendous time and mental efforts. Thus, studies to extract (segment) areas automatically using computers have been conducted vigor-
ously, especially in the areas of the lungs and brain [1, 2]. In this paper, an automated area extracting (segmenting) method using multislice CT images [3] focusing on the liver region is proposed.

Since surrounding tissues having the same CT values as the liver exist in the past automated methods for extracting the liver region from abdominal contrasted CT images, differentiating the borders between the liver and other organs has been difficult, posing a problem [4, 5]. Although this problem can be avoided by applying such methods as seed growing [6], snake [7], or deformable model [8], the problem cannot be handled easily and extraction becomes difficult in cases of large contact or border areas.

Thus, the authors consider differentiating the contact areas, which is a problem, by not only using a single three-dimensional image but also using the time-variable information of the contrast medium circulation in two three-dimensional images (the first and second time phases) differing in imaging time phases.

It is currently possible to image the entire liver twice during the time a patient holds his breath once by using multislice CT [3]. Thus, it has become possible to use two three-dimensional images differing in the state of circulation of the contrast medium, with accurate positions without special corrections. The authors use images of two time phases imaged immediately and 10-plus minutes after the infusion of the contrast medium. First, images with the liver region emphasized are generated by analyzing CT value changes due to the contrast medium in the liver region. Next, the liver region is extracted from these images by a morphology procedure. Final corrections of the liver region are performed by a three-dimensional component-connecting procedure considering the geometric characteristics of the blood vessels and tumors within the liver region. An automated liver region extraction method more reliable than the past methods is realized by the proposed method.

2. Problems of Past Methods

The problems of the past methods are discussed here. Figure 1 shows histogram examples representative of each time-phase image used in this study. The histogram of the first time-phase image imaged immediately after the infusion of the contrast medium [Fig. 1(c)] shows CT values almost the same as those of other tissues (fat, muscle) because the contrast medium has not yet infiltrated the liver region. The histogram of the second time-phase [Fig. 1(d)], obtained more than 10 min after the infusion of the contrast medium, reveals CT values of the liver region higher than those of other tissues. Methods using contrasted CT images corresponding to the second time-phase images have previously been proposed [4, 5]. Specifically, the threshold value for extracting the liver region from a histogram is first estimated. Next, the image is binarized by means of estimated threshold value and the area obtained is corrected by a morphology filter [10]. If unnecessary areas in contact with the liver region are minimized sufficiently, effective area extraction is possible even with the past methods, although the reliability of area extraction by the past methods is insufficient, since in reality these unnecessary areas are not small in many cases.

In this paper, a scheme using not only these two three-dimensional images separately, but also the information of the two three-dimensional images simultaneously, is considered in order to reduce essentially unnecessary areas having CT values the same as those of the liver. Specifically a method of extracting the liver region more accurately than in the past by tracing temporal changes of the CT value of the liver region between images is proposed.

3. The Proposed Scheme

Here, the method of analyzing the CT value changes between two time-phase images is discussed. In this paper, a two-dimensional characteristic (feature) space having the CT values of the first phase on the x-axis and the CT values of the second phase on the y-axis is considered. A two-dimensional histogram clearly reflecting the frequencies of the CT values of the two three-dimensional images in this space is shown in Fig. 2. The lighter area in the space is the high-frequency area. If there are no changes in the CT values between the two images, its voxels are distributed on
the line $y = x$. However, since the CT values of the liver increase in general in the second phase, a distribution state differing from that of the other tissues is shown (by the arrow in Fig. 2). The proposed scheme uses the distribution of the CT values of the liver region in this two-dimensional characteristic (feature) space. In considering the state of this distribution, elements other than the liver region are also numerous in the histogram, reflecting the CT values of the entire image as shown in Fig. 2, which hinders accurate understanding. Thus, more accurate information is obtained by using histograms reflecting only the CT values within the VOI (volume of interest) by establishing a fixed three-dimensional area (VOI) that takes account of the position of the liver within a CT image.

The proposed scheme has the following two steps:

1. generation of emphasized liver-region image
2. liver region extraction

The first step consists of analyzing the CT value changes of the liver inside the two-dimensional characteristic (feature) space and generating an image emphasizing the liver region from the result of analysis. This image is normalized such that the voxel value takes a value from 0 to 1, with a value of 1 representing the highest likelihood that the voxel belongs to the liver. This is called a liver likelihood image, from the point of view of expression of the likelihood of association of voxels with the liver. The method of generating a liver likelihood image in the scheme using single-phase images, the scheme using images of two phases, and the scheme using differential images between the first and second phases, is explained sequentially below. The second step of the proposed scheme is to determine the liver region from the liver likelihood image. Next, the method extracts an area as the liver region by using the geometric shape characteristics of tissues such as blood vessels and tumors. These steps are explained in order below.

### 3.1. Generation of liver likelihood image

#### 3.1.1. Method for generating a liver likelihood image from a single-phase image

The method for generating a liver likelihood image using only a single-phase image is first formalized. Let $I_1(x)$ and $I_2(x)$ be CT images of the first and second phases, respectively. Here, $x = (x, y, z)$ represents the voxel position. Figure 3(c) shows a histogram within the VOI area in the

![Figure 2](image1.png)

**Fig. 2.** 2D histogram. X axis: CT value of the first phase. Y axis: CT value of the second phase. (Arrow: region corresponding to CT values of the liver.)

![Figure 3](image2.png)

**Fig. 3.** Examples of likelihood functions. (a) Volume of Interest (VOI) in the first phase image. (b) VOI in the second phase image. (c) Histogram of VOI using (b). (d) Likelihood function estimated from (c). (e) 2D histogram of VOI. (f) Likelihood function estimated from (e).
second phase image; the CT values of the liver region are distributed around a certain value as the center. We assume that this histogram of the liver region is a one-dimensional Gaussian function such as that shown in Fig. 3(d) and we define this as the liver likelihood function. Using this likelihood function, the likelihood images \( Y_1(x) \) and \( Y_2(x) \) in the scheme using only images of the first and second phases are expressed by means of this likelihood function as follows:

\[
Y_1(x) = e^{-\frac{(t_1(x) - \overline{t_1})^2}{2\sigma_1^2}}
\]

\[
Y_2(x) = e^{-\frac{(t_2(x) - \overline{t_2})^2}{2\sigma_2^2}}
\]

Here, \( \overline{t_1} \) and \( \overline{t_2} \) and \( \sigma_1 \) and \( \sigma_2 \) represent the mean CT values and standard deviations within an interval of three times the half-value amplitude, with the highest frequency CT value within the VOI region in both phases as the center. In \( Y_1(x) \) and \( Y_2(x) \), the voxel value is 1, and the voxel value whose CT value coincides with the mean CT value represents the greatest liver likelihood.

### 3.1.2. Method for generating liver likelihood image from differential images

A method of using a differential image between two images is next considered as a scheme using images of two phases. The differential image \( I_{1-2}(x) \) is given by

\[
I_{1-2}(x) = I_1(x) - I_2(x)
\]

The likelihood image \( Y_{1-2}(x) \) is then defined as

\[
Y_{1-2}(x) = e^{-\frac{(I_{1-2}(x) - \overline{I_{1-2}})^2}{2\sigma_{1-2}^2}}
\]

Here, \( \overline{I_{1-2}} \) and \( \sigma_{1-2} \) represent the mean value and the standard deviation within an interval of three times the half-value amplitude, with the highest frequency value within the VOI region as the center.

### 3.1.3. Method for generating likelihood liver image from images of two phases

Next, a scheme expanding the concept of Section 3.1.1 two-dimensionally is formalized. As shown in Fig. 3(e), the CT values of the liver show changes different from those of the other tissues, concentrated in a certain area in the two-dimensional histograms of the liver region. In this study, this distribution is assumed to be a two-dimensional Gaussian function and is defined as the likelihood function, just as in the one-dimensional case. The likelihood image \( Y_{1+2}(x) \) using two phases is expressed as

\[
Y_{1+2}(x) = L(v)
\]

Here, \( v = \begin{pmatrix} I_1(x) \\ I_2(x) \end{pmatrix} \), and the likelihood function \( L(v) \) is expressed as

\[
L(v) = e^{-\frac{1}{2}(v - \overline{v})^T \Sigma^{-1} (v - \overline{v})}
\]

\( \overline{v} \) and \( \Sigma \) are the mean and covariance matrices within an area of three times the half-value amplitude, with the highest frequency value of the two-dimensional histogram within the VOI region as the center. Figure 3(f) shows the estimated likelihood function.

The state of distribution of the CT values of the liver region varies significantly among individual patients. In particular, it is influenced by the state of the original CT value distribution of each patient in the two-dimensional characteristic (feature) space and the infiltration rate of the

![Fig. 4. Examples of the 2D histograms of different patients.](image-url)
contrast medium (Fig. 4). The scheme proposed in this paper can absorb these differences through an automatic estimation of the variations in the state of distribution of the CT values for these patients, which is made by converting the state of the liver CT value distribution into a likelihood image.

### 3.2. Liver region extraction

The scheme for estimating the final liver region from the likelihood images discussed in the preceding section is now explained. The areas that are the targets of extraction of this scheme are summarized in Table 1. The normal liver region is estimated as the first step and the final liver region is determined by extracting the blood vessels, tumors, and so on as the second step.

The established values of the parameters contained in the method explained below are shown in Table 2. These parameters are determined by considering the magnitude of each organ to be extracted (minimum tumor size: 5 pixels in diameter, corresponding to 6.7 mm under the imaging conditions of this paper) by consulting with radiologists. In addition, all operations in the scheme discussed below are performed three-dimensionally.

#### 3.2.1. Estimation of normal liver region

Here, the extraction of the liver region is considered. First, each likelihood image $Y(x)$ such as that shown in Fig. 5 obtained in Section 3.1 is binarized by certain fixed thresholds ($T_1$, $T_2$, $T_{1,2}$, $T_{1+2}$) to obtain an image such as that shown in Fig. 6(a). Unnecessary regions in contact with the contour of the liver region are eliminated by performing an opening procedure$^*$ (with the kernel as $S_1$) on the image obtained. In addition, small empty holes due to variations in the CT values and small blood vessels inside the liver are filled by a closing procedure$^†$. As a result, a liver region such as that shown in Fig. 6(b) can be extracted. In addition, through this procedure, the fine blood vessels within the liver region are included in the liver region and comparatively large round areas such as tumors remain as empty holes.

#### 3.2.2. Extraction of blood vessels and tumors within liver region

Next, high-contrast-medium-concentration blood vessels and tumors, which are not extracted by the procedures of the preceding section, are extracted. The procedure discussed here is not performed in the scheme using only first phase images, which is not affected by the contrast

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$^*$Dilation operation (dilating an area) by the same size after erosion (contracting an area).

$^†$Eroding operation by the same size after dilation.

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<table>
<thead>
<tr>
<th>Table 1. Organs extracted by our method</th>
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<td>Extracted parts</td>
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<td>Liver</td>
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<td>Blood vessels (portal)</td>
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<td>Tumors (high concentration)</td>
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<th>Table 2. Parameter values used in our experiments</th>
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<td>$T_{\text{area}}$</td>
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<td>$T_{\text{cyst}}$</td>
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<td>VOI</td>
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(* Experiments were conducted with threshold values of 15 steps in Section 4.1.

The above values were used as $T_2$ and $T_{1+2}$ in Section 4.2.

(**) $lx$ and $ly$ are the vertical and horizontal sizes of an image.

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Fig. 5. Likelihood image estimated from Figs. 3(a) and 3(b).
medium. In addition, the following procedure is performed using second phase images $I_2(x)$.

First, dilation and erosion procedures are performed on the liver image of Fig. 6(b) obtained in the preceding step, and the dilated liver area expanding the liver region [Fig. 7(a)] and the eroded liver area contracting the liver region [Fig. 7(b)] are defined.

Next, the added blood vessel and tumor candidates are extracted by a threshold value $(I_2 + k\sigma_2)$; see Table 2 for the value of $k$). Labeling of the connected components in the extracted area is performed. The methods of extracting blood vessels and tumors from these candidates are explained separately.

First, a masking procedure is performed on the dilated liver region with respect to the above areas for blood vessels. The blood vessels outside the liver region are eliminated from the liver region. Among individual connected components, the candidates passing through the eroded liver region are extracted as blood vessels. This is because comparatively fine blood vessels within the liver region are incorporated into the liver region by the opening and closing procedures of the preceding section and the fine parts of the blood vessels extracted here pass through the eroded liver region. Thus, the blood vessels are added to the liver region by this operation [Fig. 8(a)].

Next, the method of extracting tumors is explained. Among the candidates extracted, candidates having parts overlapping with the dilated liver region are considered. The candidates outside the liver are excluded from the targets of extraction by this operation. The sphericity [9] of the remaining candidates is computed, using the fact that the shapes of tumors in general are spherical. However, in measuring the sphericity, a phenomenon of reduction of sphericity occurs in cases in which true lesions are in contact with other true lesions or undesired areas (e.g., ribs) [as indicated by the arrow in Fig. 8(b)]. In order to avoid this state, in computing the sphericity of each candidate for candidates with small sphericities, erosion-processing of the candidate and separation of contact areas are considered. This operation is performed in $E_m$ kinds for cases in which the contact areas are large. The reliability of extraction of true tumors is thus improved (Fig. 9). A tumor candidate extracted by this processing is restored to its original size by a dilating procedure, using a kernel identical to that of the erosion procedure. In addition, in threshold processing a sphericity ($T_{sphere}$), a threshold value of the volume ($T_{area}$) is also established simultaneously and fine connected components which are divided finely are excluded. By this operation, a tumor is added to the liver region [Fig. 8(b)].

Since low-concentration tumors represented by cysts show constant low CT values due to the water inside them, a fixed threshold value is established separately ($T_{cyst}$) and extraction is performed using a method identical to that used for high-concentration tumors.
4. Evaluation Methods

Imaging of CT images is done using a Light Speed QX/I multislice helical machine \(^*\) at 0.8 s/rotation. Two-phase CT images of the entire liver are imaged while the patient holds his breath after the infusion of an iodine contrast medium (300 mg I/ml) at a rapid rate of 5 ml/s through an arm vein, to a total dose of 2 ml/kg. The time required for CT imaging of all liver arteries of one phase is 10.5 s, and the interval between two imaging steps is 5 s. Thus, the total time required for imaging the two phases is 26 s. In addition, in examinations of individual patients, the time for imaging of the first phase is determined by measuring the time required for a contrast medium test infused in a dose of 15 ml to reach the abdominal aorta from the vein.

For evaluations, nine cases (two phase portions of images of a size of 512 \(\times\) 512 \(\times\) 159 [FOV\(^†\) = 36.5 cm, slice thickness = 2.5 mm, reconstructed interval = 1.25 mm]) are used, and images contracted to half (256 \(\times\) 256 \(\times\) 147) are used after three-dimensionalizing the voxel size of these images. Tumors were nonexistent in the CT images of one out of the nine cases, while at least one tumor existed in other cases. As correct solution data, the three-dimensional liver region extracted manually by radiologists was used.

The method of using only first-phase images and the method of using only second-phase images are evaluated as the conventional methods, and the method of using differential images of the first and second phases is used as the scheme employing two-phase images. Figure 10 shows the relationships in principle between these schemes and the proposed scheme. The conventional methods using only single phases are methods of estimating the likelihood function as a one-dimensional Gaussian function from the histograms simply projected onto the axes of Figs. 10(a) and 10(b) in the two-dimensional characteristic (feature) space. The methods using differential images are methods of extracting areas by focusing on only the changes in the CT values due to the effects of a contrast medium, without considering the inherent CT values of tissues. This is a scheme for estimating the likelihood function as a one-dimensional Gaussian function from the histogram projected onto the axis of Fig. 10(c). The proposed scheme considers both the effects of the contrast medium and the inherent CT values of the liver region, and estimates the likelihood function encompassing the liver region directly as shown in Fig. 10(d).

Receiving operating characteristic (ROC) analyses are used for comparison. The true positive fraction (TPF) and the false positive fraction (FPF) are defined as follows:

\[
TPF = \frac{A_C \cap A_R}{A_R} \\
FPF = \frac{A_C \cap \overline{A_R}}{A_C}
\]  

(6)

Here, \(A_R\) is the area selected by a radiologist, and \(A_C\) is the area selected by a computer. These evaluations are performed three-dimensionally. The following two points are considered in the comparisons:

1. Evaluations in the likelihood image step
2. Evaluations in the final liver region step

The evaluation methods are discussed in detail below. Each parameter is completely fixed at the values of Table 2 in the evaluations. The position of the VOI shown in Fig. 3 is also fixed in all cases.

4.1. Likelihood image evaluation method

If a likelihood image is generated using an original image unaltered, a problem associated with the accurate analysis of CT value changes within the liver region arises due to artifacts of CT images, unevenness of infiltration of

\(^*\)GE Yokogawa Medical, Tokyo. Imaging parameters: detection configuration: 4 \(\times\) 2.5 mm, “HS” mode (pitch 6), table translation speed 15 mm/rotation, 129 kV, 270 mA.

\(^\dagger\)Field of View (size of imaging range of image [length of one side]).
the contrast medium, and so on. Thus, the liver region is smoothed in advance by a smoothing procedure using a Gaussian filter (with a standard deviation $\sigma$) on an original image. However, excessive smoothing poses a danger of changing the shape of the liver. Thus, in order to study the trade-off, the smoothing parameter ($\sigma$) of an image is established in five steps ($0, 0.67, 1.34, 2.68, 5.36$ mm), an image of each phase is smoothed, and the likelihood image in each scheme is generated. Equation (6) is computed by threshold value processing (varying $T_1, T_2, T_{1+2}, T_{1-2}$) of the likelihood image obtained in multiple steps (1000 steps). A set of (FPF, TPF) is obtained by threshold processing, an ROC curve is generated by plotting all points of (FPF, TPF), and the likelihood image is evaluated.

4.2. Final liver region evaluation

Important parameters in obtaining the final liver region are the threshold values $T_1, T_2, T_{1+2}, T_{1-2}$ for obtaining the normal liver region from the likelihood image. Performance can be expected to be improved in subsequent processing by establishing these values appropriately. Thus, the likelihood image is threshold processed at a multiple number of steps (15 steps) and the liver extraction is performed. (FPF, TPF) are obtained using the final liver region, and an ROC curve is generated for evaluation.

5. Results

5.1. Likelihood image evaluation results

Figure 11 shows the results. The cases in which smoothing has been performed show better results in all schemes than the cases in which smoothing has not been performed. This confirms that smoothing is an effective means. However, it has been found that $\sigma = 1.34$ to $\sigma = 2.68$ mm is optimal with consideration of the danger of changing the shape of the liver by smoothing to an unnecessary extent, and of the ratio of improvement of performance on an ROC curve. Comparisons of the likelihood image steps of each scheme show that overall, the proposed scheme gives results clearly superior to the other schemes.

The main focus of the method using the difference between images is the difference in CT values between images or the CT value changes due to the contrast medium. Thus, there are many tissues in which the contrasting pattern due to a contrast medium is the same as that of the liver, while their CT values differ from those of the liver region, so that the performance of this method is inferior to that of the other methods.

Fig. 11. ROC curves for each method using the likelihood image. (a) Conventional method (the first phase). (b) Conventional method (the second phase). (c) Method using subtracted image. (d) Proposed method.
5.2. Final liver region evaluation results

The smoothing parameter of an original image is fixed at $\sigma = 2.68$ in comparing the final liver extraction results considering the results of the preceding section. Figure 12 shows the results of comparing the ROC curves. The conventional methods show performance significantly improved over the results of Fig. 11, indicating the efficacy of subsequent processing up to the point of obtaining the liver region from the likelihood image. However, comparisons of the overall results reveal that better results are obtained by the proposed scheme.

It should be noted here that the ROC curves are the averages of nine cases, without expressing the variance of

the data. Figure 13 shows the results of expressing the variance of the data. The results obtained with the conventional method indicated by the arrows show significant aberrations from the distribution, which can be regarded as failures in extraction. Specifically, two out of nine cases may be considered to be failure cases.

Figure 14 shows typical results of area segmentation. First, the conventional methods (first phase) show the stomach in contact with the liver region, with their border unrecognizable, in the first-phase image of Fig. 14(a). The border of the two tissues became clearer in the second phase due to the effect of the contrast medium. Thus, while the conventional methods (first phase) failed in isolating the region, the proposed scheme accurately isolated the region by using two phases. In addition, since the variations (standard deviation) in the CT value distribution of the liver region are large in general due to the effect of the contrast medium, the range of CT values determined for the liver region must be large in the conventional methods (second phase). However, unnecessary areas end up being segmented if the range of CT values is wide, while all of the liver region may not be segmented if the range of CT values is narrow, as shown in Fig. 14(b). The proposed method performs segmentation appropriately by also using stable information with small CT value variations of the first phase. The above-discussed results confirm the advantages of the proposed scheme, which uses the advantages of images of both phases. Figure 15 shows examples of three-dimensional representations of the liver finally obtained by the proposed scheme.

![Fig. 12. ROC curves using final segmented images (a) and enlarged view (b). The diagonal line from (FPF, TPF) = (0, 1) to (1, 0) is also shown. Arrows: the nearest thresholds from the diagonal line [conventional method using the second phase ($T_2 = 0.1$) and proposed method ($T_{1+2} = 0.05$)].](image)

![Fig. 13. Scattergram of TPF and FPF for conventional method using the second phase ($T_2 = 0.1$) and proposed method ($T_{1+2} = 0.05$). Arrows: failure samples of conventional method.](image)
6. Discussion

It is assumed that there are no positional discrepancies between the three-dimensional images of two phases in this paper. It is also considered that there are no significant positional discrepancies in using the proposed scheme, so long as imaging is done while the patient holds his breath. However, positional matching must be done in using images with time differences, which cannot be imaged while the patient holds his breath. In addition, the infiltration behavior of a contrast medium differs among patients. The proposed scheme minimizes differences in timing of imaging between patients by using the imaging protocol discussed in Section 4.

In addition, in establishing the VOI, a fixed area invariable with respect to individual patients is used by the proposed scheme. This is because the range in which the liver exists is almost constant in abdominal CT imaging images with the position of the spine as reference. The actual volume of the liver within the VOI area and the changes in the most frequent values when the size and position of the VOI area discussed in Table 1 are varied by +10 pixels (slice image size of 256 × 256) were studied for the nine cases that we have discussed. The results show that the standard deviation of the most frequent values is about 0.5 (HU) for the first-phase images and 1.2 (HU) for the second-phase images, and the volume ratio of the liver in the VOI area is 67% on average and 32% in the worst cases. This shows that information on the liver region can be extracted without problems even in worst cases.

The robustness with respect to the parameters, which is important in automatic area segmentation, has been evaluated. The most important parameters in this study are the threshold values with respect to the likelihood image, \( T_1 \), \( T_2 \), \( T_{1+2} \), and \( T_{1-2} \). An approximate shape of the liver region is determined by determining these parameters.
Since, in general, it is difficult to determine the threshold values dynamically, area segmentation is performed using fixed threshold values. It can be said that the points are concentrated densely in the left upper area on the ROC curves of Fig. 12, while variations in the performance evaluation results due to changes in the threshold values are small, and the method is robust with respect to the settings of the threshold values. The points occur more densely in the proposed scheme than in the other schemes, indicating the superiority of the proposed scheme. In addition, when the threshold values are fixed, the cases indicated by the arrows in Fig. 13 show clearly poorer results than the other cases in the conventional methods (second phase). The proposed scheme shows small variations in all cases. Thus, the proposed scheme can isolate unnecessary areas from the liver region in a more stable way than the conventional method. From this point of view, the proposed scheme may be considered superior to the conventional methods in automatically segmenting the liver area.

Improving the performance of differentiation of tumors occurring in the contour area or noncircular tumors, which have been excluded from this study, remains as a future task. In reality, in determining whether a radiologist extracts such tumors as the liver region or not, not only the liver region but also its accurate positional relationships with the surrounding areas and the shape of the liver itself must be considered. In improving performance in this respect, a method that constructs a model of the shapes of the liver region and the surrounding areas and performs matching with this model is needed.

The authors are planning to apply the proposed scheme to clinical measurement of the liver volume in liver transplants. Thus, the stability of the scheme with respect to changes in the imaging protocol, allowing it to be used in various hospitals, must be tested. Since the time of imaging is expected to differ when images imaged under different protocols are used, there is a possibility that the infiltration time of the contrast medium will also change. The authors plan to evaluate how this would influence the likelihood image.

7. Conclusions

An automatic liver region segmentation method using time-variable information between images of two phases differing in the circulatory state of a contrast medium is proposed in this paper. This method evaluates CT value changes of the liver region on a two-dimensional histogram accurately and generates a liver likelihood image. It determines the liver region from this image, segments blood vessels, tumors, and so on, by using their geometric characteristics, and determines the final liver region. The results of applying the method to nine cases show that the proposed method gives more consistent and better segmentation results than the conventional methods and confirms the efficacy of using information from different phases.

Matching positions between these images is currently being studied [11, 12] in order to effectively use in addition the information from phases that are difficult to image while a patient holds his breath. The correspondence relationships of all three-dimensional images obtained by one-time examinations can be determined by this approach, and it can be used not only for segmenting the liver region, but also in automatically differentiating tumors [13].

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