AUTOMATIC LIVER SEGMENTATION USING MEAN-SHIFT TECHNIQUES

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Abstract—**In this paper, I present an auto context model (ACM)-based automatic liver segmentation algorithm, which combines ACM, multiatlases, and mean-shift techniques to segment liver from 3-D CT images. Our algorithm is a learning-based method and can be divided into two stages. At the first stage, i.e., the training stage, ACM is performed to learn a sequence of classifiers in each atlas space (based on each atlas and other aligned atlases). With the use of multiple atlases, multiple sequences of ACM-based classifiers are obtained. At the second stage, i.e., the segmentation stage, the test image will be segmented in each atlas space by applying each sequence of ACM-based classifiers. The final segmentation result will be obtained by fusing segmentation results from all atlas spaces via a multi classifier fusion technique. Specially, in order to speed up segmentation, given a test image, I first use an improved mean-shift algorithm to perform over segmentation and then implement the region-based image labeling instead of the original inefficient pixel-based image labeling. The proposed method is evaluated on the datasets of MICCAI 2007 liver segmentation challenge. The experimental results show that the average volume overlap error and the average surface distance achieved by ourmethod are 8.3% and 1.5 m, respectively, which are comparable to the results reported in the existing state-of-the-art work on liver segmentation.**

Index Terms—Auto context model (ACM), fuzzy integral, liver segmentation, mean shift, multi classifier fusion, multiple atlases.

I. INTRODUCTION

ACCURATE segmentation of liver tissue from medical imagesis an essential and crucial step for computer-aidedliver disease diagnosis and surgical planning. Among the variousmedical imaging techniques, computed tomography (CT)images are often used for these purposes, thanks to their highersignal-to-noise ratio and better spatial resolution.HoIver, liver segmentation from CT images is a challengingtask, due to the high-intensity similarity betIen liver tissue andadjacent organs, the highly varying shape of the liver, and thepresence of severe pathologies.

So far, numerous methods have been proposed for liver segmentationfrom CT images, such as those based on statisticalshape models (SSMs) [1]–[5], those based on probabilistic atlases [6]–[8], those based on deformable models [9]–[20],those based on graph-cuts [21], those based on region growing[22], [23], threshold-based methods [24], [25], rule-basedmethods [26], and learning-based methods [27]–[29]. Also, severalgood reviews can be found in [30] and [31].

Among all these liver segmentation methods, the SSM-basedmethods are currently the main automatic liver segmentationmethods. Kainmuller et al. [2] employed SSM in combination with a model of the typical intensity distribution around theliver boundary and neighboring structures. The SSM consistedof around 7000 landmarks and was built from an extensive trainingset of 112 liver shapes. The required correspondences Iredetermined using a semiautomatic method, where the principalridges of each liver Ire specified manually. Heimann et al. [3]incorporated SSM with an evolutionary algorithm to provideinitialization for a deformable mesh that searches for humanliver boundaries. The underlying SSM consisted of 2500 landmarksand was built automatically from 35 training shapes.Correspondences Ire determined by a population-based optimizationapproach. Zhang et al. [4] presented an approach forautomatic liver segmentation from CT scans, which was basedon a SSM integrated with an optimal surface detection strategy. In their work, a 3-D generalized Hough transform was employed to detect approximate location of the liver shape model. Afterthe SSM initialization, the shape model was deformed to adaptto the liver contour through an optimal surface detection basedon graph theory. Although the three SSM-based methods aforementionedperform Ill on liver segmentation, they require acomplicated and time-consuming model construction process.

Recently, the auto context model (ACM) has been proposed in [32] to automatically segment subcortical structures frombrain images. It integrates image appearances together with thecontext information (implicit shape model) by learning a seriesof classifiers. The classifier may choose two types of features:1) image appearance features computed on the local imagepatches; and 2) context features from a large number of siteson the classification maps. Given a set of training images andtheir corresponding label maps, the first classifier is learnedbased on image appearance features. The classification mapscreated by the current classifier are then used as context information,along with image appearance features, to train thenext classifier. The algorithm iterates to make the classificationmaps approximate the ground truth. In testing, the algorithm followsthe same procedure by applying the sequence of learnedclassifiers to compute the classification maps. In [32], ACM hasbeen proven poIrful for brain image segmentation (both singlestructure segmentation and whole brain segmentation).

More recently, an ACM and multi atlases-based segmentation framework has been proposed for prostate

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segmentation fromCT images [33] and hippocampus segmentation from MR images[34], and got very impressive results. Motivated by theauthors of [32]–[34], in this paper, I present an ACM-basedalgorithm for automatic liver segmentation from 3-D CT images, by using ACM, multi atlases, and mean-shift techniques. I try to apply the ACM and multi atlases-based segmentation framework described in [33] and [34] to liver segmentationfrom CT images and moreover an improved mean-shift over segmentation is used to speed up segmentation. Specifically, inthe training stage, ACM is performed to construct a sequenceof classifiers in each atlas space (based on each atlas and otheraligned atlases).With the use of multiple atlases, I can obtain multiple sequences of ACM-based classifiers. In the segmentation stage, the test image will be first aligned onto each atlasspace, and then segmented by the corresponding sequence ofACM-based classifiers. The final segmentation result will beobtained by fusing multiple segmentation results from multipleatlases via a fuzzy integral-based multi classifier fusion. Furthermore,in order to speed up segmentation, given a test image,I first use an improved mean-shift algorithm to perform over segmentation and then implement the region-based imagelabeling instead of the original inefficient pixel-based imagelabeling. The proposed method is evaluated on the datasets ofMICCAI 2007 liver segmentation challenge. The experimentalresults show that our method is comparable to the state-of-the art works on liver segmentation in terms of both accuracy andefficiency.

The main contribution of this paper is threefold: First, I introduce the ACMand multi atlases-based segmentation frame work into liver segmentation from 3-D CT images. Second, Iuse the fuzzy integral to fuse the segmentation results frommultiple atlas spaces. Third, an improved mean-shift over segmentation is employed to speed up liver segmentation.

The remainder of this paper is structured as follows:Section II describes the proposed ACM-based liver segmentationalgorithm in detail. Section III evaluates the proposedmethod on the datasets of MICCAI 2007 liver segmentationchallenge. Section IV concludes the paper.

II. METHOD

In this section, I present in detail the proposed ACM-basedliver segmentation algorithm. The ACM integrates image appearancestogether with the context information (implicit shapemodel) by learning a series of classifiers, which avoids complicatedprocedures to construct an explicit SSM, and it has beensuccessfully applied to brain and prostate segmentation. Thus,in this paper, I try to employ ACM as the primary tool forautomatic liver segmentation from 3-D CT images.

A. Learn the Classifiers in Each Atlas Space by ACM

In the learning stage, a set of abdominal 3-D CT training images {Xj } and the corresponding manual liver labels {Yj }are employed as the training set, where j = 1, . . . , m. Eachtraining image is treated as an atlas and our task is to constructa sequence of classifiers by ACM in each atlas space.

To construct the sequence of classifiers in the space of one atlas Xa , the other (m − 1) atlases Xb s need to be aligned with Xa by affine registration and the corresponding manual liverlabels are also aligned. Thus, the set of abdominal CT training images {aXj } and the corresponding manual liver labels {aYj }in the space of Xa are obtained. Based on {aXj } and {aYj },I are able to construct the sequence of classifiers in the space of Xa by ACM.

1) Training of ACM: **Similarly to [32], ACM first constructs a training set**

$$S = \{(ayji, aXj(Ni)),\ j = 1, \ldots, m,\ i = 1, \ldots, n\} \quad (1)$$

where m is the number of training images, n is the number ofpixels in each image, ayji is the class label for pixel i in image aXj , and aXj (Ni) denotes the local image patch centered atpixel i in image aXj . The first classifier is learned based on theimage appearance features computed on the local image patchesa Xj (Ni). For each training image aXj , the classification maps Pj are then computed by the learned classifier. The algorithmthen constructs a new training set

$$S' = \{(^{a}y_{ji}, (^{a}X_j(N_i), P_j(i))), j = 1, \ldots$$

Where Pj (i) is the classification map centered at pixel i for image aXj . A new classifier is then trained, not only based on theimage features extracted from aXj (Ni), but also on the context features extracted from Pj (i). Once a new classifier is obtained,the algorithm repeats the same procedure until convergence. Figure. 1 gives an illustration of the training procedure of ACM.Finally, ACM outputs a sequence of learned classifiers

$$p(t)(yi\ /X(Ni),\ P(t-1)(i)),\ t = 1, \ldots, T \quad (3)$$

where P(0) is a uniform distribution, and thus the context featuresare not selected by the first classifier, i.e.,

$$p(1)(yi/X(Ni),\ P(0)(i)) = p(1)(yi/X(Ni)).$$

Due to the natural feature selection and fusion capability ofthe boosting algorithms, in this paper, I employ Ada Boost [35]as the basic classifier and I set the iteration number T = 4. The

Ada Boost classifiers automatically select and fuse importantsupporting context features, together with image appearancefeatures.The same training procedure of ACM will be performed ineach atlas space. Thus, I will obtain m sequences of learnedclassifiers, which correspond to the total m atlases.

2) **Image Appearance and Context Features:**

As aforementioned, I need to extract two types of features: 1) image appearance features; and 2) context features. In this paper, the image appearance features I employed include intensity, intensity mean, spatial positions

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(x, y, z coordinates) of the central

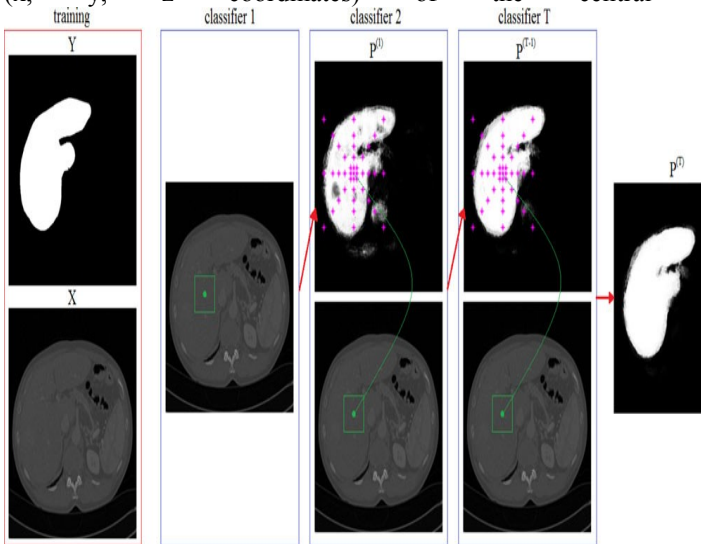

Figure. 1.Illustration of the training procedure of ACM. Given a set of abdominal CT training images and the corresponding manual liver labels, the first classifier is learned based purely on the local image appearance. The subsequent classifiers are learned not only based on the local image appearance, but also on the context features extracted from the classification map produced by the previous classifier. Objects with strong appearance cues are often correctly classified even after the first round. These probabilities then start to influence their neighbors in the next round (via context features), especially if there are strong correlations betIen them. Note that this is just a 2-D illustration. In fact, I use 3-D image and context features as detailed in Section II-A2

pixel of the local image patch, and various 3-D Haar features extracted from the local image patch. The image patch size I used is $7 \times 7 \times 7$.The 3-D context features are obtained from the 3-D classificationmaps, which is similar to the 2-D context feature extractionin [32]. For the 2-D applications in [32], eight rays in 45◦ intervals I restretched out from the current pixel of interest andthe 2-D context locations Ire sampled on these rays. In thecase of our 3-D liver segmentation application, I extend the2-D operation into the 3-D case, i.e., for each pixel of interest,26 rays in directions of 26 neighbors are stretched out from thecurrent pixel and a radius sequence (0, 1, 3, 5, 7, 10, 12, 15, 20,25, 30, 35, 40, 45, 50, 60, 70, 80, 90, 100, 125, 150, 175, 200)is then used for sparsely sampling the 3-D context locations oneach ray. The classification probabilities on these locations areused as context features (both individual probabilities and themean probabilities within a $3 \times 3 \times 3$ window). Figure. 2 gives anillustration. The context features play a very important role in3-D liver segmentation, due to the relatively fixed positions ofabdominal anatomical structures.

B. Multiatlases-Based Liver Segmentation

1) Liver Segmentation in Each Atlas Space: In the segmentationstage, given a test image X test , our task is to segment X test in each atlas space. Let us take the space of atlas Xa, for example. First the test image X test will be aligned onto the space of Xa to obtain the aligned test image a X test. Then, a X test will be segmented (each pixel in a X test will be labeled) by the correspondingsequence of ACM-based classifiers in the space of Xa to obtain a classification map a Y test . Note that the segmentingprocedure of ACM follows the training procedure of ACMby applying the sequence of learned classifiers to compute theclassification maps, as shown in Figures. 3 and 4.

2) Results Fusion by Fuzzy Integral: The same segmentingprocedure will be conducted in each atlas space as describedin Section II-B1. Thus, I will obtain m final classificationmaps, corresponding to the total of m atlases. Finally, the mclassification maps will be first transformed onto the originaltest image space, and then fused together by a multiclassifierfusion technique.

In this paper, I adopt the Choquet fuzzy integral [36] to fusethe classification maps from multiple sequences of classifiers.Fuzzy integral is a nonlinear fusion method in a decision making

environment. It considers both the evidence supplied by eachclassifier and the importance of each subset of classifiers (via afuzzy measure). Due to the non additivity of the adopted fuzzymeasure, it can also represent the interaction among differentclassifiers. Fuzzy integral, as an aggregation tool in multi classifier fusion, has been widely used for pattern recognition, objectclassification, and object history matching [37], [38].

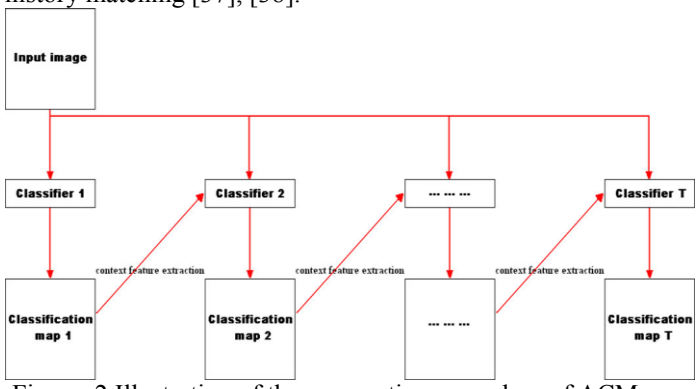

Figure. 2.Illustration of the segmenting procedure of ACM.

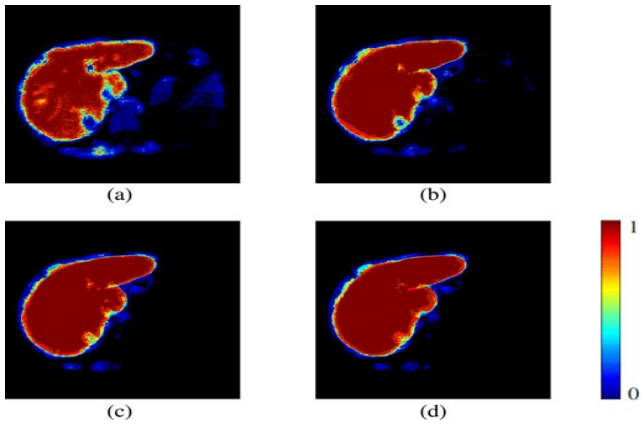

Figure. 3. Classification map of liver at each iteration of ACM. (a) Iteration 1.
(b) Iteration 2. (c) Iteration 3. (d) Iteration 4.

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C. Region-Based Labeling Using the Improved Mean-Shift Over segmentation

Pixel-based image labeling is not efficient because it has toscan every pixel in the image. Especially, in our multi atlases based segmentation framework, it also has to scan the imagemany times.

In order to speed up segmentation, I use region-based image labeling instead of pixel-based image labeling. Specifically,given a test image, I first use the mean-shift algorithm [43] to perform over segmentation, to obtain a series of irregular imageregions. For each region, a set of pixels (around 5%) are thenrandomly selected to perform classification. I take the average of the classification probabilities of these sampled pixels as theprobability of the region (assigning all pixels in the region with such a probability).

Also, in the training stage, I can use only the sampled pixelsin all regions to train theclassifiers, which drastically reducesthe training time.

However, due to the high intensity similarity betIen liver tissue and adjacent organs (such as heart and stomach) in abdominalCT images, sometimes even the standard mean-shift over segmentation cannot separate them. Figure. 5 gives an illustrationof the standard mean-shift over segmentation. As I can see from Figure. 5, the intensities of the liver and the adjacentheart are highly similar, which makes it difficult toseparate the liver from the heart by the standard mean-shiftalgorithm

In order to tackle such a problem, I introduce prior probability as an additional feature for the mean-shift algorithm. Inthis way, leakage of image regions pertaining to the liver into surrounding tissue can be avoided. The prior probability map isobtained by taking the average of aligned manual liver labels ofall the training images. In other words, during the over segmentation stage, I attempt to separate liver tissue from adjacent organs(such as heart and stomach) based on empirical knowledgederived from all known manual liver labels. Specifically, I apply the 5-D mean-shift over segmentation using three dimensions for the x, y, z coordinates, onedimension for intensity andone dimension for prior probability. The kernel I used is the uniform one. Figure. 6 gives an illustration of the improved mean shift over segmentation. As I can see from Figure. 6, although theimproved mean-shift algorithm further over segments the image, it can separate Ill the liver tissue from the heart (based onempirical knowledge).

D. Outline of the Algorithm

Here, I give the outline of our final algorithm. In training,given a set of abdominal CT training images (atlases) alongwith the corresponding manual liver labels, ACM is performedto learn a sequence of classifiers in each atlas space (basedon each atlas and other aligned atlases). Thus, after training,multiple sequences of ACM-based classifiers are obtained. Intesting, given a test image: 1) Align the test image onto each atlasspace. 2) In each atlas space, over segment the aligned test imageusing the improved mean-shift algorithm to obtain a series ofirregular image regions. 3) Perform region-based classificationusing the corresponding sequence of ACM-based classifiers.4) Obtain the final segmentation result by fusing all classificationresults from all atlas spaces by the fuzzy integral. Note that, practically, I perform mean-shift over segmentation only in one atlas space. The over segmentation results in other atlasspaces can be achieved by applying an affine transformation betIen the atlases.

III. EXPERIMENTS

A. Experimental Data and Setup

I evaluate our learning-based liver segmentation methodon the training and testing datasets of MICCAI 2007 liver segmentation challenge (http://www.sliver07.org). There are 20contrast-enhanced abdominal CT images in the training datasets,and 10 in the testing datasets. All images have a spatial resolutionof 512 × 512 pixels in each transversal slice and the pixelspacing varies from 0.55 to 0.9 mm. The inter slice distance varies from 0.5 to 5 mm.

Figure. 5. Illustration of the standard mean-shift over-segmentation. (a) One original transversal slice. (b) Over segmentation result using the standard mean-shift algorithm.

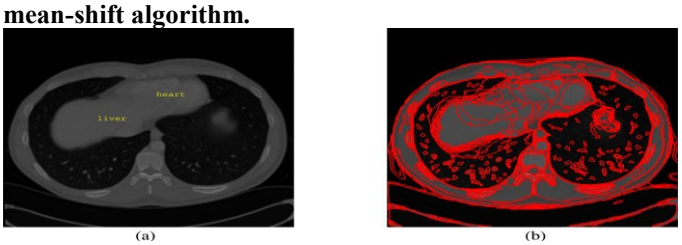
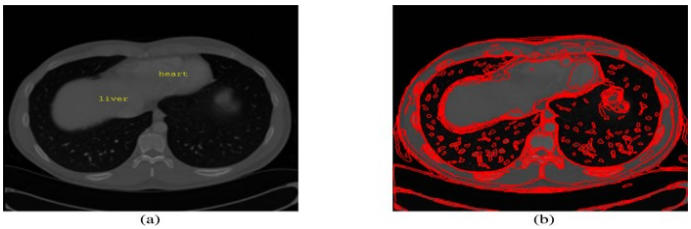


Figure. 6. Illustration of the improved mean-shift over segmentation. (a) One original transversal slice. (b) Over segmentation result using the improved mean-shift algorithm.

B. Experimental Results

***1) Qualitative Results*:** In this section, I demonstrate the qualitative evaluation of our method (ACM + Multi atlases +mean-shift). I compare our method with the methods using Only ACM and using ACM in the multi atlases based framework. Note that, for the method using only ACM, I randomly select one atlas space and learn the classifiers by ACM in that space.For fair comparison, the same parameters are employed in ACMfor all the methods. The comparison results are shown in Figure. 7.From Figure. 7, I can observe that the segmentation results bythe method using ACM in the multi atlases-based framework are closer to the manual reference segmentations than those bythe method using only ACM, and the segmentation results byour method are comparable to those by the method using ACM in the multi atlases-based framework. However, our method is significantly faster as detailed in the next section.



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***2) Quantitative Results*:** For quantitative evaluation of ourmethod, the following five evaluation metrics from theMICCAI 2007 workshop [30] are adopted: volumetric overlaperror, signed relative volume difference, average symmetric surface distance (DAvg), root mean square symmetric surface distance (DRMS), and maximum symmetric surface distance(DMax). I also include runtime as an additional measure forefficiency evaluation.

IV. CONCLUSION

In this paper, I have presented an ACM-based algorithmfor segmenting liver from 3-D CT images. Specifically, by combining ACMs and a multi atlases technique, multiple sequences
of ACM-based classifiers are constructed, and further used forliver labeling. The final segmentation result will be obtained byfusing multiple segmentation results from multiple sequencesof classifiers via a fuzzy integral based multi classifier fusion. Inorder to speed up segmentation, I also introduce an improved mean-shift algorithm to over segment the test image and subsequentlyperform a region-based image labeling instead of theoriginal inefficient pixel-based image labeling. The proposed method has been evaluated on the datasets of MICCAI 2007
liver segmentation challenge. The experimental results showthat our method is comparable to the state-of-the-art work onliver segmentation in terms of both accuracy and efficiency.

REFERENCES

[1] H. Lamecker, T. Lange, and M. Seebaee, "Segmentation of the liver usinga 3D statistical shape model," Zuse Inst., Berlin, Germany, Tech. Rep.04–09, pp. 1–25, 2004.
[2] D. Kainmuller, T. Lange, and H. Lamecker, "Shape constrained automatic segmentation of the liver based on a heuristic intensity model," inProc. Mid. Image Comput. Comput.-Assisted Intervention Workshop 3-DSegmentation Clinic Grand Challenge, 2007, pp. 109–116.
[3] T. Heimann, H.-P.Meinzer, and I. Wolf, "A statistical deformable modelfor the segmentation of liver CT volumes," in Proc. Mid. Image Comput.Comput.-Assisted Intervention Workshop 3-D Segmentation Clinic GrandChallenge, 2007, pp. 161–166.
[4] X. Zhang, J. Tian, K. Deng, Y.Wu, and X. Li, "Automatic liver segmentationusing a statistical shape model with optimal surface detection," IEEETrans. Biomed. Eng., vol. 57, no. 10, pp. 2622–2626, Oct. 2010.
[5] H. Badakhshannoory and P. Saeedi, "A model-based validation schemefor organ segmentation in CT scan volumes," IEEE Trans. Biomed. Eng.,vol. 58, no. 9, pp. 2681–2693, Sep. 2011.
[6] H. Park, P. Bland, and C. Meyer, "Construction of an abdominal probabilisticatlas and its application in segmentation," IEEE Trans.Med. Imag.,vol. 22, no. 4, pp. 483–492, Apr. 2003.
[7] X. Zhou, T. Kitagawaa, K. Okuo, T. Hara, H. Fujita, R. Yokoyama,M. Kanematsu, and H. Hoshi, "Construction of a probabilistic atlas forautomated liver segmentation in non-contrast torso CT images," Int. J.Comput. Assist. Radiol.Surg., vol. 1281, pp. 1169–1174, 2005.
[8] D. Furukawa, A. Shimizu, and H. Kobatake, "Automatic liver segmentation based on maximum a posterior probability estimation and levelset method," in Proc. Mid. Image Comput. Comput.-Assisted InterventionWorkshop 3-D Segmentation Clinic Grand Challenge, 2007, pp. 117–124.
[9] L. Gao, D. Heath, and E. Fishman, "Abdominal image segmentation usingthree-dimensional deformable models," Investigative Radiol., vol. 33,no. 6, pp. 348–55, 1998.
[10] L. Soler, H. Delingette, G. Malandain, J.Montagnat, N. Ayache, C. Koehl,O. Dourthe, B. Malassagne,M. Smith,D.Mutter, and J. Marescaux, "Fullyautomatic anatomical, pathological, and functional segmentation from CTscans for hepatio surgery," Comput. Aided Surg., vol. 6, no. 3, pp. 131–142,2001

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