Gastroenterology Report, 6(3), 2018, 239–241

doi: 10.1093/gastro/goy028
Advance Access Publication Date: 31 July 2018
Commentary

COMMENTARY

Soft-tissue-segmentation methods during image-guided precision liver surgery

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Introduction

Image-guided liver surgery is the current direction in which 'precision surgery' is developing [1]. Clinical doctors can extract the structural information of the liver and perform a geometric analysis of the liver shape using the liver-segmentation technique. This technique provides data for subsequent procedures, including measuring the volume, evaluating the function, locating the lesions and planning the surgery. Nonetheless, the structural extraction and segmentation of the liver are still mostly based on manual outlining of layers in liver CT images, which is subjective and inefficient. In recent years, many methods on automatic segmentation of the liver have been proposed and examined [2]. The liver is an organ rich in sharp edges and concaves, and it lacks gray contrast with adjacent tissues; meanwhile, various diseases can occur in the liver, and different degrees of liver diseases can significantly affect the acute segmentation of the liver parenchyma. We have sorted out our own images in clinical practice and classified them for readers to clearly understand the impact of different lesions on liver-segmentation accuracy, as shown in Figure 1. Therefore, the precision segmentation of the liver remains one of the greatest challenges facing the field of medical image processing.

Results and discussion

Although the segmentation methods based on the deformation model, statistical shape model and probabilistic atlas model have been widely used in the field of liver segmentation and tested to be effective, the following problems remain to be addressed [3]. (i) In the deformation model, the validity and robustness of the internal and external force constraint models must be improved. In addition, deformation models usually cannot achieve accurate segmentation of convex or concave regions while maintaining smoothness. (ii) In the statistical shape model, precision matching between a priori shape models is relatively difficult, and the initial contour must be optimized. Meanwhile, how to use the personalized information of the images to be segmented to construct the statistical shape model remains a problem. (iii) In the probabilistic atlas model, subjectivity exists during the construction of the atlas. Accurate and precision matching between the probabilistic atlas and CT image of the liver area to be segmented warrants further improvement.

In recent years, researchers have found that sparse coding (or sparse dictionary learning) methods were able to sparsely represent the training samples of statistical models, effectively remove redundant information of training samples and simplify the computation of the statistical shape model, thereby increasing the efficiency of segmentation [4]. However, the segmentation methods based on sparse coding only generated a sparse model under the framework of Euclidean space and performed dictionary learning via Euclidean distance analysis; thus, they exhibited the following limitations: (i) Similar image

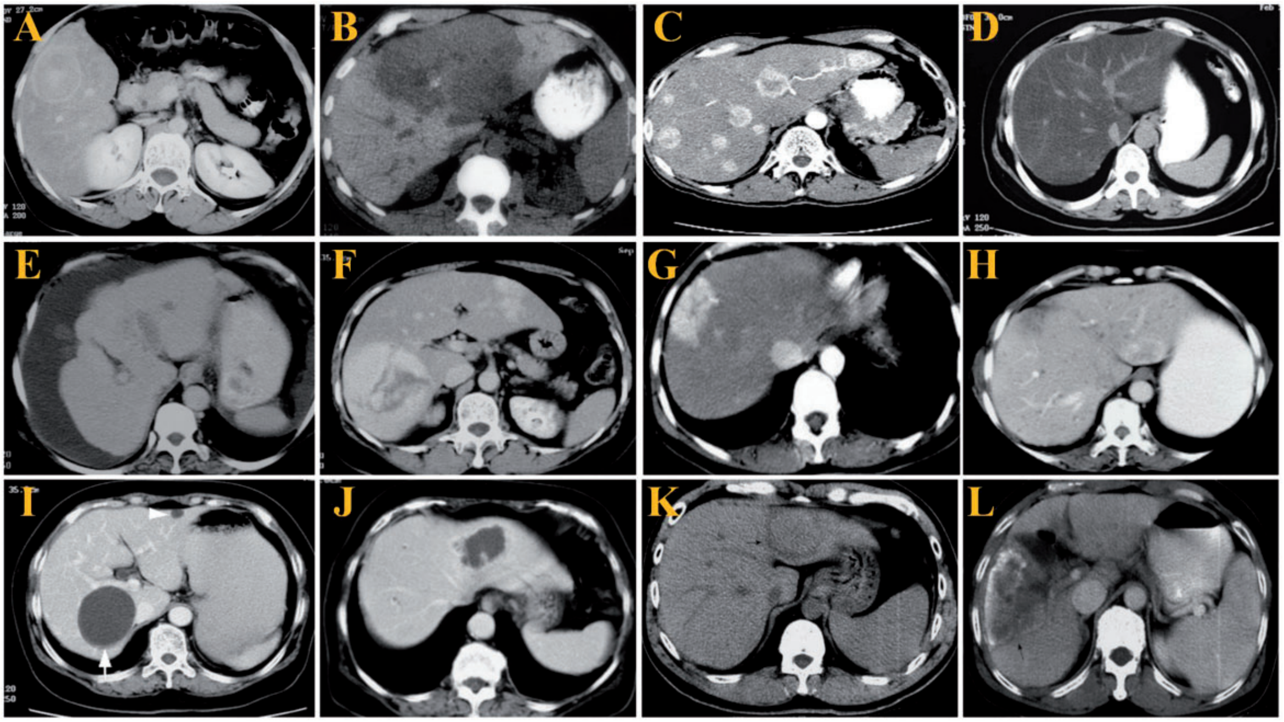

Figure 1. Comparison between the liver and adjacent soft tissues in gray contrast-enhanced computed tomography images. (A) Primary hepatic cancer. (B) Fibrolamellar hepatocellular carcinoma. (C) Metastatic hepatic cancer. (D) Fatty liver. (E) Cirrhosis. (F) Hemangioma. (G) Hepatic focal nodular hyperplasia. (H) Hepatic angiomyolipoma. (I) Liver cyst. (J) Liver abscess. (K) Hepatic adenoma. (L) Hepatic infarction.

blocks were required to set up sparse matrix and dictionary learning during the process of sparse model construction. In that case, similarity and matching accuracy between small image blocks were difficult to obtain and various degrees of gap or an overlapping region may appear in the segmentation results, which negatively affects the segmentation accuracy. (ii) When using the discrete cosine transformation (DCT) dictionary to acquire the similarity levels of images, it is difficult to achieve optimization.

When processing medical data, the sample space can be represented in a curved Riemannian manifold to better interpret the sample. As a result, many researchers further investigated the symmetric positive define (SPD) matrix and generated a non-Euclidean, curved Riemannian manifold. This Riemannian manifold provided a compact representation of the target model, incorporated multiple features of images and achieved a robust visualization of the size and shape of the target [5]. Based on the Riemann manifold theory, the SPD matrix can be mapped to the tangent space through logarithmic mapping and calculated accordingly; then, the final algorithm results can be obtained through the index operator mapping back to the original space, during which the shortcomings in statistical learning methods can be addressed or avoided.

According to relevant research progress, research on liver segmentation based on CT images has greatly promoted advancements in the diagnosis and treatment of clinical diseases. However, existing algorithms have not yet fully addressed many technical segmentation problems, including the complexity of the abdominal anatomy, various liver diseases, imaging interference of abdominal CTs and individual patient differences. The liver-segmentation methods based on statistical models exhibited a reliable efficacy and received improvement from many researchers, but many disadvantages remain [6, 7]. Therefore, a reliable and consistent segmentation method is still considered a global challenge and thus warrants further study by scholars to construct a liver-segmentation method suitable for clinical applications.

Conclusions

Liver segmentation based on statistical learning represents the future direction of 'precision surgery' development. In particular, the successful application of brain-like algorithms based on deep learning theory and the popular statistical learning theory of Riemann will be an important foundation for the breakthrough of liver-segmentation technology in the future.

Acknowledgements

This work was supported by the Beijing Natural Science Foundation (No. L172055), the Beijing Municipal Science & Technology Commission Research Fund (No. Z171100000417004) and the China Postdoctoral Fund (No. 2018M631755).

References

1. Fonio P, Calandri M, Faletti R *et al*. The role of interventional radiology in the treatment of biliary strictures after paediatric liver transplantation. *Radiol Med* 2015;**120**:289–95.
2. Stokbro K, Aagaard E, Torkov P *et al*. Surgical accuracy of three-dimensional virtual planning: a pilot study of bimaxillary orthognathic procedures including maxillary segmentation. *Int J Oral Maxillofac Surg* 2016;**45**:8–18.
3. Norajitra T, Maier-Hein KH. 3D Statistical shape models incorporating landmark-wise random regression forests for omni-directional landmark detection. *IEEE Trans Med Imaging* 2017; **36**:155–68.

4. Coupé P, Manjón JV, Fonov V *et al*. Patch-based segmentation using expert priors: application to hippocampus and ventricle segmentation. *NeuroImage* 2011;**54**:940–54.
5. Cherian A, Sra S. Riemannian dictionary learning and sparse coding for positive definite matrices. *IEEE Trans Neural Netw Learn Syst* 2017;**28**:2859–71.
6. Wang X, Yang J, Ai D *et al*. Adaptive mesh expansion model (AMEM) for liver segmentation from CT image. *Plos One* 2015;**10**:e0118064.
7. Wang X, Zheng Y, Gan L *et al*. Liver segmentation from CT images using a sparse priori statistical shape model (SP-SSM). *Plos One* 2017;**12**:e0185249.