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A homotopy-based sparse representation for fast and accurate shape prior modeling in liver surgical planning

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ABSTRACT

Shape prior plays an important role in accurate and robust liver segmentation. However, liver shapes have complex variations and accurate modeling of liver shapes is challenging. Using large-scale training data can improve the accuracy but it limits the computational efficiency. In order to obtain accurate liver shape priors without sacrificing the efficiency when dealing with large-scale training data, we investigate effective and scalable shape prior modeling method that is more applicable in clinical liver surgical planning system.

We employed the Sparse Shape Composition (SSC) to represent liver shapes by an optimized sparse combination of shapes in the repository, without any assumptions on parametric distributions of liver shapes. To leverage large-scale training data and improve the computational efficiency of SSC, we also introduced a homotopy-based method to quickly solve the $L1$-norm optimization problem in SSC. This method takes advantage of the sparsity of shape modeling, and solves the original optimization problem in SSC by continuously transforming it into a series of simplified problems whose solution is fast to compute. When new training shapes arrive gradually, the homotopy strategy updates the optimal solution on the fly and avoids re-computing it from scratch.

Experiments showed that SSC had a high accuracy and efficiency in dealing with complex liver shape variations, excluding gross errors and preserving local details on the input liver shape. The homotopy-based SSC had a high computational efficiency, and its runtime increased very slowly when repository's capacity and vertex number rose to a large degree. When repository's capacity was 10,000, with 2000 vertices on each shape, homotopy method cost merely about 11.29s to solve the optimization problem in SSC, nearly 2000 times faster than interior point method. The dice similarity coefficient (DSC), average symmetric surface distance (ASD), and maximum symmetric surface distance measurement was 94.31 ± 3.04%, 1.12 ± 0.69 mm and 3.65 ± 1.40 mm respectively.

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1. Introduction

Primary liver cancer is one of the most life-threatening cancers around the world. In China, liver cancer is the second leading source of cancerous death, with a mortality rate of 26.26 per 100,000 people (Chen and Zhang, 2011). Among the variety of treatment methods, liver transplantation and liver resection are the most effective ones (Sotiropoulos et al., 2009). Considering the lack of available liver from cadaver, living donor liver transplantation (LDLT) is very important to extend the scarce donor pool (Broelsch et al., 2000).

A detailed knowledge of liver anatomy plays a key role in the determination of surgery strategy for LDLT. The volume of transplanted liver portion should be sufficient for the recipient and the remaining portion should be as large as possible to minimize trauma to the donor. Besides, since anatomies of intrahepatic vessels and tumors vary enormously among different patients, surgeons need to learn the location of the liver portion that would be cut off, together with the distribution of intrahepatic vessels and tumors before the surgery to achieve the best proposal for resection. As a result, preoperative planning based on medical image is highly helpful for the accuracy and safety of liver surgery.

Segmentation of liver from preoperative images is a key module in liver surgical planning. However, two important factors put forward a big challenge for accurate and robust segmentation of

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liver in clinical environment (Heimann et al., 2009). First, the low contrast and week boundary information in medical images can easily lead to mis-segmentation. For example, gray levels of the liver and its adjacent tissues are very similar, which renders the boundary hard to detect. Second, intrahepatic tumors often cause inhomogeneous gray levels and misleading boundaries, so these tissues may not be successfully preserved in segmentation results. These factors make prior information about liver shapes highly significant for accurate segmentation.

Shape prior-based approaches are more stable against local image artifacts than traditional methods that solely rely on low-level appearance cues. For instance, shape prior has been widely incorporated into watershed (Hamarneh and Li, 2009), geodesic active contours (Leventon et al., 2000), level set (Cremers et al., 2007; Rousson and Paragios, 2000), graph cuts (Vu and Manjunath, 2008), and it plays an important role in robust segmentation of a variety of organs such as left ventricle (Zhu et al., 2009), kidney (Xie et al., 2005), liver (Heimann et al., 2006), prostate (Ghose et al., 2012, 2010), and brain structures (Shen et al., 2001), etc.

In the application of liver surgical planning, there are two important requirements on shape prior modeling for liver. First, the shape prior should be patient-specific and accurate enough. This is because liver shapes from different individuals have very complex variations, and tumors often make liver shapes more complex. A patient-specific shape prior should contain enough prior information about a specific patient, otherwise the complex liver shape variations may lead to a big difference between shape priors and actual liver shapes for the patients, in which case the inaccurate shape priors will not help segmentation process so well. In addition, the shape prior modeling process should be scalable and efficient. Accurate liver shape modeling requires a large-scale training data and high number of vertices on liver shapes. To be applicable in clinical environment, the shape prior modeling method should remain a low-level of time consumption when training data and vertex number increase to a large scale. In addition, in many cases training shapes are collected gradually. When new training shapes arrive, the model should be updated on the fly with a high requirement on efficiency.

One of the most popular shape prior modeling methods is to use statistical shape models (SSM) to learn the priori information of shape variations from many training samples and employ it to represent an input shape adaptively (Heimann and Meinzer, 2009). The Active Shape Model (ASM) (Cootes et al., 1995) is widely used to deal with shapes that follow a unimodal Gaussian distribution. When shape variations are complex, a mixture of Gaussians may be able to handle them (Cootes and Taylor, 1999), assuming shapes follow a multimodal distribution. To overcome the limitation of ASM on statistical constraint, manifold learning techniques (Etyngier et al., 2007) can be employed to obtain a non-linear shape prior. Alternatively, the shape space can be divided into multiple sub-spaces in which shape distributions are more compact and easier to model. These methods include population-based and patient-specific shape statistics (Shi et al., 2008; Yan et al., 2011; Zhang et al., 2011), hierarchical ASM (Davatzikos et al., 2003), and subject-specific dynamical model (Zhu et al., 2009), etc.

In the recent years, sparse representation has proven to be extremely powerful to obtain a compact high-fidelity representation of the observed signal. It has also been increasingly used in a lot of image processing applications (Wright et al., 2010), where using sparsity as a prior led to state-of-the-art results. Gao et al. (2012) proposed a sparse representation based classification method and applied it to prostate segmentation. Shi et al. (2014) employed a patch-based sparse representation in neonatal atlas construction and successfully recovered more anatomical details. Sparse Shape Composition (SSC) (Zhang et al., 2012a) is a recently proposed method for shape prior modeling. It does not need any assumption on shapes' parametric probability distribution but can effectively model complex shape variations. It is also able to capture gross errors in the input shapes and preserve local details even when they are not statistically significant in the repository (Zhang et al., 2012a). Due to these advantages, SSC has been successfully applied in cardiac motion analysis (Yu et al., 2013), lung localization and other applications (Zhang et al., 2012a). It also showed a great advantage in robust liver shape modeling (Wang et al., 2013). However, its computational efficiency may be limited by increasing repository's capacity and number of vertices on each shape. To obtain efficient shape modeling, one may decrease the repository's capacity or the number of vertices, but the accuracy will also be reduced. Dictionary learning method can improve the speed of computation by reducing redundancy of the shape repository (Zhang et al., 2012b). However, the dictionary still inevitably loses important shape information and it needs to be updated every time when new shapes are added to the repository.

A widely-used optimization scheme to solve SSC is the interior point method. It can achieve the optimal solution conveniently but has a high complexity, which precludes its application when the problem is on a large-scale (Beck and Teboulle, 2009). Gradient-based methods are more efficient since they usually make use of the sparsity of the problem. For example, the iterative shrinkage-thresholding algorithm (ISTA) and the fast iterative shrinkage-thresholding algorithm (FISTA) have been successfully used in signal/image processing with fast speed (Beck and Teboulle, 2009). Other fast $L1$-minimization algorithms include the augmented Lagrange multiplier (ALM) method (Afonso et al., 2011), iteratively reweighted algorithms (Chartrand and Wotao, 2008), and primal–dual algorithms (Chambolle and Pock, 2011), with their application in image restoration, reconstruction, denoising, etc. Homotopy (Foucart and Rauhut, 2013) is substantially faster than interior point method. It continuously transforms the $L1$ optimization problem into a series of simplified problems whose solution is fast to compute (Malioutov et al., 2005). Homotopy is more efficient than other methods such as FISTA and ALM in sparse representation problems of face recognition (Yang et al., 2010). It has also been used as a highly effective way to solve the $L1$ optimization problem in many other fields, such as the recovery of streaming signals (Asif and Romberg, 2013) and highly undersampled image reconstruction (Trzasko and Manduca, 2009).

On the other hand, in many medical imaging applications such as liver image segmentation based on statistical shape models, training shapes may not come in on batch. This is because it is hard to obtain a training shape with a large number of vertices in real-time, and constructing an informative shape repository with a large capacity is extremely time consuming. As a result, new training shapes are gradually added to an existing shape repository. In this case, the optimization of shape modeling should be updated when new training shapes come. A direct way to solve this problem is to re-compute the optimal solution using the expanded repository, disregarding the solution obtained from the previous repository. However, this method has a low efficiency. A better way is to take advantage of the previous solution and compute the new one in a faster speed.

The combination of SSC and homotopy was preliminarily investigated by Wang et al. (2014). However, the property of homotopy and SSC was not discussed in detail. In this paper, we study the applicability of homotopy-based SSC in liver shape modeling to a further degree and investigate its performance when updating the modeling on the fly. The new method can improve the accuracy of SSC-based liver shape modeling by using a large-scale training data and high number of vertices on each shape. The runtime of the new method just increases very slowly when the scale of training samples and the number of vertices grow to a large scale. In

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