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Automatic X-ray landmark detection and shape segmentation via data-driven joint estimation of image displacements

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ABSTRACT

In this paper, we propose a new method for fully-automatic landmark detection and shape segmentation in X-ray images. To detect landmarks, we estimate the displacements from some randomly sampled image patches to the (unknown) landmark positions, and then we integrate these predictions via a voting scheme. Our key contribution is a new algorithm for estimating these displacements. Different from other methods where each image patch independently predicts its displacement, we jointly estimate the displacements from all patches together in a data driven way, by considering not only the training data but also geometric constraints on the test image. The displacements estimation is formulated as a convex optimization problem that can be solved efficiently. Finally, we use the sparse shape composition model as the a priori information to regularize the landmark positions and thus generate the segmented shape contour. We validate our method on X-ray image datasets of three different anatomical structures: complete femur, proximal femur and pelvis. Experiments show that our method is accurate and robust in landmark detection, and, combined with the shape model, gives a better or comparable performance in shape segmentation compared to state-of-the art methods. Finally, a preliminary study using CT data shows the extensibility of our method to 3D data.

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1. Introduction

In clinical practice, X-ray radiography is widely used for various purposes due to its convenience and low cost. Segmenting shape contours such as femur and pelvis benefits many applications, such as computer aided disease diagnosis (Chen et al., 2005; Lindner et al., 2012), image based surgery planning and intervention (Gottschling et al., 2005). In addition, 3D reconstruction of anatomical models can also be performed with the segmented 2D contours (Baka et al., 2011; Dong and Zheng, 2008; Zheng et al., 2007, 2009a). Traditionally, shape segmentation in X-ray images, despite its extreme usefulness, is seldom done in clinical practice due to its difficulty. In cases where it is ever done, it is carried out manually by doctors, which is both time-consuming and error-prone. Therefore, in this paper our attention is on fully-automatic techniques, which will immediately make this traditionally useful but difficult task widely applicable. However, automatic segmentation of X-ray images faces many challenges. The poor and non-uniform image contrast, along with the noise, makes the segmentation very difficult. Occlusions and the overlap between bones make it difficult to identify local features of bone contours. Furthermore, the existence of implants often drastically changes the visual appearance of the relevant anatomical regions.

A typical pipeline of X-ray segmentation consists of two steps: landmark detection and shape regularization (Lindner et al., 2012, 2013), as depicted in Fig. 1. In this paper we also follow this pipeline. Given an image, we first detect the positions of a set of landmarks which are defined along the shape contour. Then, the landmark detection output is regularized using a statistical shape model. In this way, the final contour is controlled by both the image cue encoded in the landmark detection output, and the shape prior information conveyed in the statistical shape model.

In the above pipeline, accurately detecting landmarks is crucial for a good segmentation performance. In this paper, we propose a new method for this task. We estimate the displacements from a set of randomly sampled local image patches to the landmark based on patch appearance, and the individual predictions are then combined in a voting scheme to produce the predicted landmark position. In previous methods, the displacement from each patch to the landmark is estimated independently using a pre-trained model. Our method is fundamentally different, as we jointly

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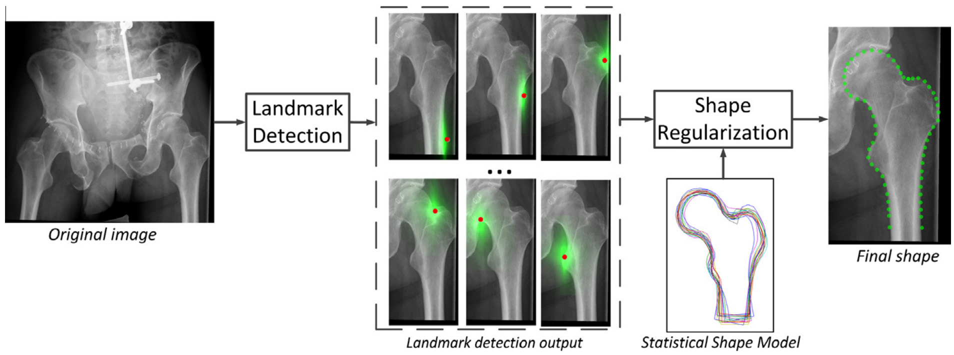

Fig. 1. The general pipeline of shape segmentation which is composed of two steps: landmark detection and shape regularization.

estimate the displacements from all patches to landmarks together in a data-driven way. This joint estimation scheme allows us to exploit the mutual interactions among the displacements that are being estimated by considering the geometric relations between the patches in the test image. Combining the information from training data and the geometry constraints, our displacement estimation method achieves better accuracy.

After landmark detection, these predicted landmark positions are regularized by a statistical shape model to get the final segmented shape contour. In this paper we exploit the sparse shape composition model (Zhang et al., 2011a), which is shown to be better than classical PCA based shape models.

We tested our method on large and challenging datasets involving three anatomic structures: complete femur, proximal femur and pelvis. These datasets contain a considerable amount of images with an implant and images with low contrast. In the experiments, we show that both the landmark detection method and the shape regularization improve the performance, and that by combining them together we get better or comparable results compared to other methods. Finally, we also performed a preliminary 3D study using CT data to show the 3D extensibility of our method.

The paper is organized as follows: We first briefly summarize the related work in Section 2. Then, in Section 3 we introduce our new landmark detection algorithm, followed by Section 4 which presents the shape regularization method using the sparse shape composition model. The experiments are presented in Section 5. We conclude the paper in Section 6.

2. Related work

In recent literature, there has been a considerable amount of work in landmark detection. Some methods utilize low-level image features such as gradients and edges (Chen et al., 2005; Cristinacce and Cootes, 2008; Smith et al., 2009). For example, Chen et al. (2005) locate candidate femoral shafts and heads by detecting parallel lines and circles. This type of methods often suffers from the large appearance variation and image noise encountered in X-ray images. To alleviate this problem, some similar methods such as (Bergtholdt et al., 2010; Donner et al., 2010; Gamage et al., 2010; Schmidt et al., 2007) incorporate the topological constraints in a model-based way, where they search for the best configuration of the model given the image cue revealed by the low-level image features.

To overcome the challenge of appearance variation, some machine learning based methods have been proposed which have shown promising performance. For example, in (Zheng et al., 2007; Dong and Zheng, 2008, 2009), a particle filter-based approach is first used to determine the morphological parameters, and then a belief propagation based approach is used to extract contours from multiple calibrated X-ray images. Zhou and Comaniciu (2007) introduce the so-called shape regression machine to segment in real time the left ventricle endocardium from an echocardiogram of an apical four chamber view. Zheng et al. (2008, 2009b) use marginal space learning for localizing the heart chambers, and then estimate the 3D shape through learning-based boundary delineation.

In recent years, random forest (RF) (Breiman, 2001) based methods are becoming more and more popular. RF (Breiman, 2001) was originally proposed for general classification or regression, and the class-specific Hough forest was presented in (Gall and Lempitsky, 2009) for object detection. Since then, RF has shown very promising results in tasks related to landmark detection or organ localization in medical data (Criminisi et al., 2010; Lindner et al., 2012, 2013). The basic idea is as follows: First, some local patches are sampled in the image. Then, the displacements from the patches to the landmark are estimated by RF regression. Finally, the landmark position is estimated by a voting scheme considering the individual estimations from all the patches. Pauly et al. (2011) localize organs in MR images using Random Ferns which has a similar idea with RF except that a fern systematically applies the same decision function for each node of the same level of the tree. There are two key components behind the success of RF-like voting based methods. The first is the strategy of positioning landmarks by estimating its relative displacements with regard to other image parts. Here the fact of medical image being highly structured is exploited to improve the localization using relational displacement prediction. The second is the discriminative power of the RF model. In this paper, we follow the framework of predicting relational displacements from image patches. However, instead of using RF, we propose a new method to improve the displacement prediction by a data-driven approach. The significant difference of our method is that we predict the displacement of test patches not only by comparing the test patch with the training patches, but also exploit the fact that the location of these test patches are known to us and can be used to enforce a geometric constraint on the displacements: the displacement from different patches to a common landmark position should be consistent with the geometric relation between the test patches. By utilizing this information as a regularization on the displacement being predicted, we improve the prediction accuracy.

Recently, Donner et al. (2013) proposed a new landmark detection method by combining the RF-based prediction with the high-level topological relation between the landmarks, and they get very good results on X-ray images and 3D CT data. First, RF classification and regression give the candidates for each landmark, and then an MRF model encoding the global configuration of landmarks is employed to get the final landmark positions. This method aims at disambiguating landmark candidates using a global model *on top of* the individual landmark predictions, which is especially suit-

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