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An external field prior for the hidden Potts model with application to cone-beam computed tomography

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HIGHLIGHTS

- External field prior improves image segmentation accuracy.
- Manual segmentation of one image is used as a prior for subsequent images.
- Applicable to longitudinal imaging, such as image-guided radiation therapy.

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ABSTRACT

In images with low contrast-to-noise ratio (CNR), the information gain from the observed pixel values can be insufficient to distinguish foreground objects. A Bayesian approach to this problem is to incorporate prior information about the objects into a statistical model. A method for representing spatial prior information as an external field in a hidden Potts model is introduced. This prior distribution over the latent pixel labels is a mixture of Gaussian fields, centred on the positions of the objects at a previous point in time. It is particularly applicable in longitudinal imaging studies, where the manual segmentation of one image can be used as a prior for automatic segmentation of subsequent images. The method is demonstrated by application to cone-beam computed tomography (CT), an imaging modality that exhibits distortions in pixel values due to X-ray scatter. The external field prior results in a substantial improvement in segmentation accuracy, reducing the mean pixel misclassification rate for an electron density phantom from 87% to 6%. The method is also applied to radiotherapy patient data, demonstrating how to derive the external field prior in a clinical context.

1. Introduction

Longitudinal imaging is a popular method in a wide range of scientific fields including environment, economics, agriculture, biology, and medicine. Remote sensing is used for long-term monitoring of land use (Strickland et al., 2011), water quality (McClain, 2009) and economic growth (Henderson et al., 2011). X-ray computed tomography (CT), magnetic reso-

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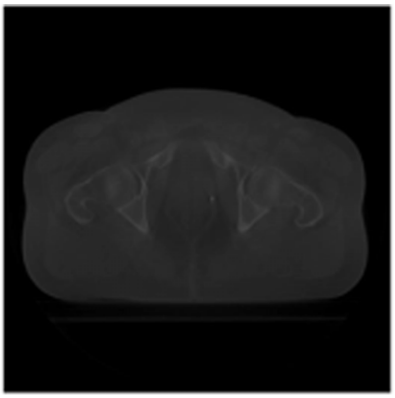
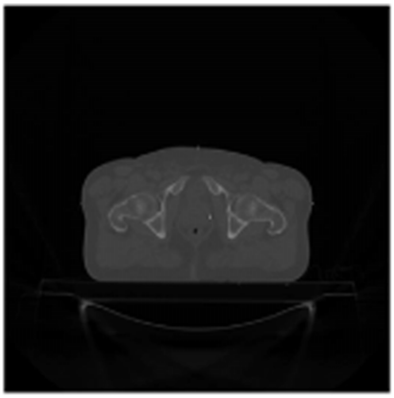


(a) Cone-beam CT scan.



(b) Fan-beam CT scan.

Fig. 1. Comparison of axial slices from a pre-treatment, cone-beam CT scan and a reference, fan-beam CT scan of a radiotherapy patient. The cone-beam CT scan has higher spatial resolution but lower contrast-to-noise ratio.

nance imaging (MRI) and ultrasound are used for *in vivo* studies of livestock production (Alston et al., 2007), tumour progression (Albanese et al., 2013) and neurodegenerative disease (Thompson et al., 2004). These images can exhibit artefacts and distortions such as cloud cover in remote sensing, magnetic field inhomogeneities in MRI and X-ray scatter in CT. The resulting poor contrast-to-noise ratio (CNR) creates difficulties in interpreting the images. Multiple images acquired of the same subject increase the information available compared to that obtained from a single acquisition. In order to perform well in this setting, an image processing algorithm must efficiently incorporate all of the available knowledge that characterises the specific types of images encountered.

In this paper we focus on a specific example of longitudinal imaging: daily cone-beam CT scans for image-guided radiotherapy. Flat-detector, cone-beam CT was introduced in the previous decade for image-guided medical interventions (Jaffray et al., 2002; Kalender, 2011). Since then, it has been widely adopted for clinical use in dental surgery, brachytherapy and external-beam radiotherapy. Cone-beam CT produces a 3D image of the patient similar to conventional, fan-beam CT. An axial slice from a cone-beam CT scan of a radiotherapy patient is shown in Fig. 1(a). For comparison, a fan-beam CT scan of the same patient is shown in Fig. 1(b). The advantage of cone-beam CT over fan-beam CT is that the X-ray source and the detector panel are mounted on retractable arms that rotate around the image subject, enabling the image to be obtained *in situ* during a medical procedure.

A drawback of cone-beam CT is that it is more susceptible to artefacts induced by X-ray scatter (Siewerdsen and Jaffray, 2001) or high density objects such as metal implants (Müller and Buzug, 2009) compared to other imaging modalities. The increased magnitude of X-ray scatter in cone-beam CT is due to the larger area that is exposed to the X-ray beam. This leads to shading artefacts that manifest as inhomogeneities in the pixel values. Metal-induced artefacts can be due to implanted gold fiducial markers or surgical clips inside the patient. These manifest as streaking and banding in the image. These distortions result in a lower CNR and thus many methods that can be successfully used for analysing conventional, fan-beam CT or other imaging modalities encounter difficulties when applied to cone-beam CT.

1.1. *Medical image segmentation*

The goal of image-guided radiotherapy is to target the delivery of a prescribed radiation dose, while avoiding nearby organs at risk (OAR) and other sensitive tissue. The individualised treatment plan for each patient is based on diagnostic-quality fan-beam CT and MRI scans. Fractionated, radiotherapeutic doses are delivered 5 days a week over a number of weeks. Thus, a significant amount of time can elapse between the creation of the treatment plan and the completion of a course of treatment. Even on a daily basis, changes in the size of the bladder and rectum in prostate cancer patients can result in displacement of the target site. To detect these changes, a cone-beam CT scan is taken *in situ*, immediately prior to irradiation. This information is currently underutilised due to the level of precision and detail required for volumetric variation analysis, coupled with the short timeframe in which the radiotherapy procedure is to be carried out in the clinic. Automated methods have the potential to aid in the decision-making process by labelling the image voxels according to tissue type, estimating the boundaries of the tumour and neighbouring organs, and highlighting any regions where changes in these boundaries might have exceeded tolerance.

Recent approaches to boundary estimation in cone-beam CT have used deformable models that evolve according to partial differential equations. The two major approaches are 3D mesh models (Costa et al., 2007) and level sets (Chen and Radke, 2009). These methods fit within the information-theoretical framework developed by Grenander and Miller (2007). Deformable template models need to be initialised very close to the boundary of interest, as they are prone to becoming stuck on local minima. Thus, they are more suited as a post-processing step to refine an approximate solution that was obtained via other means, as in Chen et al. (2009), Zhou et al. (2010) and Lu et al. (2011).