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Improving Image Quality of Cone-Beam CT Using Alternating Regression Forest

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Abstract

We propose a CBCT image quality improvement method based on anatomic signature and auto-context alternating regression forest. Patient-specific anatomical features are extracted from the aligned training images and served as signatures for each voxel. The most relevant and informative features are identified to train regression forest. The well-trained regression forest is used to correct the CBCT of a new patient. This proposed algorithm was evaluated using 10 patients' data with CBCT and CT images. The mean absolute error (MAE), peak signal-to-noise ratio (PSNR) and normalized cross correlation (NCC) indexes were used to quantify the correction accuracy of the proposed algorithm. The mean MAE, PSNR and NCC between corrected CBCT and ground truth CT were 16.66HU, 37.28dB and 0.98, which demonstrated the CBCT correction accuracy of the proposed learning-based method. We have developed a learning-based method and demonstrated that this method could significantly improve CBCT image quality. The proposed method has great potential in improving CBCT image quality to a level close to planning CT, therefore, allowing its quantitative use in CBCT-guided adaptive radiotherapy.

Keywords

Cone-beam CT; artifact correction; random forest; auto-context model

1. INTRODUCTION

Quantitative cone-beam CT (CBCT) imaging is on increasing demand for precise image guided radiation therapy since it provides a foundation for advanced image-guidance techniques, including accurate treatment setup, online tumor delineation and patient dose calculation (1, 2). With more precise treatment monitoring from accurate CBCT images, dose delivery errors can be significantly reduced in each fraction and further compensated for in subsequent fractions using adaptive radiation therapy (3-5). However, the current CBCT imaging has severe artifacts and its current clinical application is therefore limited to

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patient setup based on only bony structures. Recently, many scatter correction techniques have been proposed to improve CBCT image quality and facilitate the use of CBCT in radiation therapy. These techniques can be roughly grouped by two types: pre-processing-based methods and post-processing-based methods (2, 6). The pre-processing-based methods suppress scatter during projection data acquisition, of which the anti-scatter-grid-based and air-gap-based methods are the two most popularly ones. The post-process-based methods first estimate the scatter based on prior knowledge or statistical distribution modeling, then remove the estimated scatter from projection data, and finally reconstruct CBCT images from corrected projection data. These methods can be grouped into the following four categories: 1) measurement-based methods, 2) software-based methods, 3) hardware-based decomposition methods, and 4) hybrid methods. The existing scatter correction methods may reduce artifacts in CBCT images, but most of them could not restore the true Hounsfield Unit (HU) in CBCT images, hindering CBCT images' utility for dose calculation in CBCT-guided adaptive radiotherapy (2). To deal with this issue, we develop a learning-based approach to improve CBCT image quality for quantitative analysis during adaptive radiotherapy.

2. METHOD

Suppose we have a set of pairs of CBCT and CT training images. For each pair, CT image is used as the regression target of CBCT image to improve the CBCT quality. CBCT and CT is preprocessed by removing noise and uninformative regions. The intra-subject registration is performed to align each pair of CT and CBCT images of the same subject, and a rigid-body inter-subject registration is used to roughly map all subjects onto a common space. Then, we register all the training data to the new CBCT image. In the training stage, patch-wise multi-level features, i.e., DCT (7), LBP (8), and pairwise voxel difference with multi-scale sensitivity (9), i.e., original and down-sampled image with three down sampling factors (0.75, 0.5 and 0.25), are extracted from training CBCT. Secondly, fuzzy c-means labeling (10) is utilized to generate the corresponding CT label automatically. Combining the extracted features with CT labels, we perform a feature selection using logistic LASSO algorithm (4, 11-13) to identity the most salient and informative features with patient-specific information. Thirdly, we utilize the selected features as well as the corresponding CT targets to train a random forest using alternating regression forest (ARF) (14). During the training, we apply auto-context model (15) to incorporate the appearance information from original CBCT with the context information from the previously predicted CT for iterative refinement. In the test stage, anatomical features from the new CBCT are extracted and fed into the well-trained random forest for the prediction of an improved CBCT. Finally, we use all predicted patches together to reconstruct the final high-quality CBCT image prediction. Fig. 1 shows the brief workflow of our prediction method.

2.1 Alternating Regression Forest (ARF)

Recent studies showed the efficacy of random forest in training the regression model of medical imaging, due to its efficacy in tackling medical image processing (3, 4, 9). Classical random forest trains a bag of binary decision trees each of which is provided with a random subset of training data and trained independently from the others. The major drawback of

classical random forest is its binary decision tree is only decided locally on the node level how the data is further split, without considering the state of the whole regressor. Although this characteristic results in fast and parallel training capabilities and thus lead to low computational costs, the training procedure of random forest is not globally controlled by an appropriate metric of the regressors' performance, and the entire state of training model could not be checked and improved at each node. This makes the training procedure theoretically difficult and unintuitive to comprehend the success of learning method and unveils several practical disadvantages (16): 1) In training, there is no guarantee that all thresholds of splitting functions have been properly learned by the entire model; 2) It is difficult to apply random forest to the CBCT correction, since the extracted CBCT features are usually in a high dimensional representation space and only a small fraction of randomly chosen features could be used for binary splitting. This would diminish the performance of training, thus weaken the inference ability when a new CBCT feature arrives.

Since the classical random forest pays no attention to information loss while splitting data from parent node to child node. This work, inspired by the idea of introducing a global loss from recent ARF studies (17, 18), proposes a novel splitting procedure considering both the global and local optimization. The general learning objective can be written as a greedy stage-wise optimization:

$$\operatorname{argmin}_{\phi_d} \sum_{\{x_i, y_i\}} L(y_i, R_{d-1}(x_i, \phi) + r_d(x_i, \phi_d)) \quad (1)$$

where $L(\cdot)$ is a differentiable loss function, $R_{d-1}(x_i, \phi)$ denotes the regressor trained up to depth $d-1$, $r_d(x_i, \phi_d)$ denotes the regressor for current depth, and ϕ_d is the split threshold optimized in the depth d . At root nodes, we start with an initial regressor $R_0 = r_0(x_i, \phi)$ and add a new depth to the forest. At depth d , assume previous regressor $R_{d-1}(x_i, \phi)$ predicts training samples x_i as $R_{d-1}(x_i, \phi) = R_{d-2}(x_i, \phi) + r_{d-1}(x_i, \phi_d)$ by ensemble model according to stored samples in corresponding nodes. These predictions yield a stage-wise loss which should be minimized by Eq. (1). After optimizing thresholds, the regressor $r_d(x_i, \phi_d)$ can be determined according to information gain criterion. Since the splitting function of each node and each depth is chosen by jointly reducing the uncertainty of training data and regularizing the whole regressors' global loss, unlike the classical random forest whose path of splitting training data is independent beforehand for each node, our proposed ARF allows the splitting path to be always optimized globally and locally as we have a hierarchical splitting structure. Thus, the feedback of each depth reasonably reduces the uncertainty of binary decision tree and enhances the accuracy of the inference, as shown in Fig. 2.

2.2 Auto-context Method (ACM)

During inference, decision trees are a collection of weak learners. In order to further improve the prediction performance, the ACM (15, 19-21) is used to leverage the surrounding information with respect to the object of interest such as bone area. We use the initial ARF to create context features for all training patients, which are then used in combination with the initial extracted features to train an improved ARF. The process is

repeated to train a series of ARFs until the prediction criterion is met. It is proven that ACM can reduce the prediction error. In the testing stage, to predict the improved CBCT, the new CBCT image can follow the same concept of ACM to generate the final improved CBCT. The framework of ACM is showed in Fig. 3.

3. RESULTS

In order to test the proposed method, we applied our method to 10 patients' planning CT and CBCT data. All patients' CT data were acquired using a Siemens CT scanner ($1.0 \times 1.0 \times 1.0 \text{ mm}^3$). All patients' CBCT data were acquired using an on-board Varian kV CBCT scanner ($1.2 \times 1.2 \times 2.0 \text{ mm}^3$). We performed leave-one-out cross-validation method to evaluate the proposed high-quality CBCT correction algorithm. Our corrected CBCT images were compared with the planning CT images. The mean absolute error (MAE), peak signal-to-noise ratio (PSNR) and normalized cross correlation (NCC) (22, 23) indexes were used to quantify the correction accuracy of the prediction algorithm. PSNR is an engineering term for the ratio between the maximum possible power of signal and the power of corrupting noise that affects the fidelity of its representation (24, 25). NCC is a measure of similarity of two series as a function of the interseries displacement (13, 26).

An example of the CBCT corrected by the proposed method is shown in Fig. 4. This corrected CBCT is close to original planning CT images. Table 1 shows the MAE, PSNR and NCC of the difference between the corrected CBCT and original CT for each patient. Overall the mean MAE, PSNR and NCC are $16.67 \pm 2.58 \text{ HU}$, $37.28 \pm 1.76 \text{ dB}$ and 0.98 ± 0.01 , respectively, which demonstrated the correction accuracy of the proposed learning-based method.

4. DISCUSSION AND CONCLUSION

In this paper, we have developed a novel learning-based CBCT improvement method based on patch-based anatomical signature and auto-context alternating regression forest. The most informative signature is selected to effectively capture the relationship between the planning CT and CBCT. The novelty of our approach is to integrate auto-context model and anatomical features into a machine learning framework to iteratively predict the high-quality CBCT. This approach has 2 distinctive strengths: 1) In order to improve the random forest training efficiency, a feature selection mechanism is introduced to identify the more informative and salient features in the anatomical signature of each voxel through minimizing the logistic sparse LASSO energy function. Finally, the selected features with higher discriminative power are used to train the random forest. 2) Unlike the splitting threshold optimization in classical random forest which decided locally on node level, ARF optimizes the threshold by a global loss over all trees and reformulate the training phase of random forest as a depth-wise regressor, thus enhances prediction accuracy compared to classical random forest. Moreover, an auto-context model is used to incorporate the context information from the previously predicted CBCT image for iterative refinement of the final corrected CBCT. We have demonstrated that this method could significantly improve CBCT image quality. The proposed method has great potential in improving CBCT image quality

to a level close to planning CT, therefore, allowing its quantitative use in adaptive radiotherapy.

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Figure 1.
Schematic flow chart of the proposed algorithm for high-quality CBCT predication.

Figure 2.
The flow chart of the alternating regression forest.

Figure 3.
The framework of the ACM.

Figure 4.

The results of corrected CBCT. The images from left to right are the original CT images, the original CBCT images, the difference between CT and original CBCT, the predicted CBCT (PCBCT) using the proposed method, the difference between CT and PCBCT images.

Table 1.

The average MAE, PSNR and NCC for the all patients.

Index	MAE (HU)	PSNR (dB)	NCC
Mean $\pm$ STD	16.66 $\pm$ 2.58	37.28 $\pm$ 1.76	0.98 $\pm$ 0.01