

Low Dose CT Image Restoration Using a Localized Patch Database

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Abstract—As growing concerns on the potential side effect of radiation induced genetic, cancerous and other diseases, the low-dose CT imaging is becoming a hot issue, how to minimize the radiation exposure level while maintaining the diagnostic performance. In previous work, we have proposed a framework that is working in conjunction with image-based database. It restores a low-dose image with modified non-local means (NLM) that have expanded search window to include regular-dose priors obtained from same or different patients. In this paper, we further develop the framework to know the internal structures of CT images so that the NLM filtering is applied with more intelligent way. In addition, knowing the internal structures changes the database from image-based to patch-based that organized structure by structure. As preliminary work, this was tested to restore a structure of low-dose CT image and it showed a very promising results.

I. INTRODUCTION

RECENTLY, there has been a growing amount of research on *low-dose* CT to minimize the radiation exposure to patients. However, the lower the dose that can be achieved either by reducing the X-ray flux, measurements, or both, the lesser image quality we can get since the signal-to-noise ratio (SNR) depends on the X-ray dose quadratically. The low-dose CT images usually suffer from severe noise artifacts and reduced feature details. Consequently, developing a reconstruction tool under a minimum radiation dose level still remains a challenging problem in the CT field.

There are two approaches to solve the low-dose CT imaging problem. One enforces better image quality directly in the iterative reconstruction process in conjunction with the statistical characteristics of projection data [3]. The other performs pre- or post-processing either in projection data space or in the image domain via a suitable restoration method [1][7]. Our approach belongs to the second category, utilizing the nonlocal means (NLM) filter [1]. The NLM filter searches an expanded neighborhood (window) of a noisy pixel for similar image patches and averages the centers of these patches [4][8].

In recent work [6][7], we improved the low-dose CT image quality by applying an NLM filter that extended the search space from the low-dose image to one more regular-dose CT images obtained from the same or different patients, called priors. The method first searches a database of similar

regular-dose CT images and aligns them to the target image. With these registered regular-dose CT images as a source of clean pixels, the NLM-like filter is then applied. The key of this method to be successful is the richness of the database and the performance of the registration scheme.

Assuming we have a sufficiently good database (typically containing thousands or more CT images with sufficient diversity), how well regular-dose CT images (priors) can be aligned to a given low-dose CT image (target) will play a crucial role in the overall workflow. Even with an ideal registration method, it is important to know the internal structures of a CT image. In other words, we want to restore a structure (or an organ) in the target image by borrowing density values of the same structure in the priors. Once we know the internal structures of the priors and the target, the restoration process can proceed structure by structure with reduced potential errors such as introducing false information or eliminating true information. In this paper, we verify this idea by modifying our previous workflow to work with a localized patch-based database that collects and organizes patches (typically vary from 5x5 to 11x11) from certain structures of the priors and then restores a structure in the target with this patch set.

In the following, Section II describes the method and technical details of our low-dose CT image restoration scheme working with a localized patch-based database. Then, we will show some initial results and conclude the paper in Section III.

II. METHODOLOGY

A. Patch-Based Localized Database

Since our database contains regular-dose CT images obtained from a diverse set of patients, registration by non-rigid transformation is less likely to be successful. This turns our focus to a new, parallelizable algorithm for the efficient detection and localization of anatomical structures in CT images [2]. By using the localization algorithm, interesting anatomical structures ($c \in \mathcal{C}$) can be detected and localized by a tight bounding box parameterized as a 4-vector $\mathbf{b}_c = (b_c^L, b_c^R, b_c^A, b_c^P)$ where each component represents the position (in mm) of the corresponding axis-aligned wall¹.

The patches are extracted from the bounding boxes and organized per organ. In this study, we densely sample the patches over the prior and this operation is accelerated by GPU.

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¹ Superscripts follow standard radiological orientation convention: L=left, R=right, A=anterior, P=posterior.

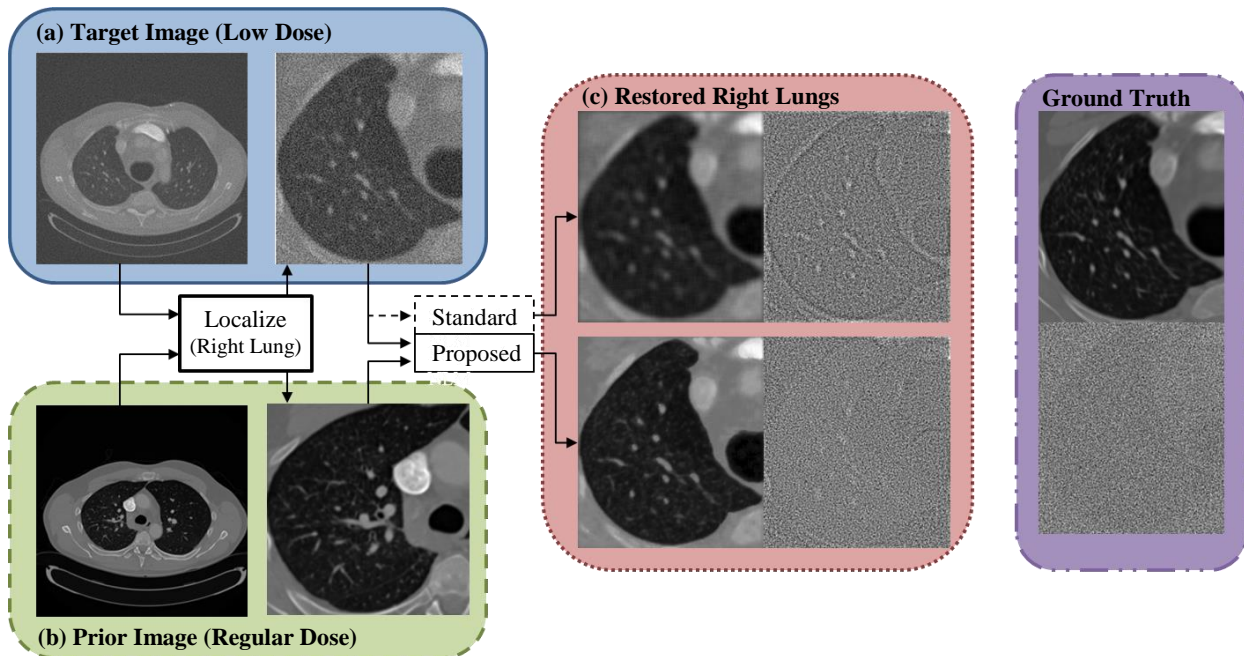


Figure 1. Low Dose CT Image Restoration with a Localized Patch Database Workflow. (a, b) the target (or the prior) images used in the experiment with localized right lung. (c) restored images with two different methods and their difference images with the target.

B. NLM Filtering with Prior Patches

Our new NLM filter is similar to the other types of NLM filters except that it operates on a number of similar patches obtained from the same organs or structures than the target, rather than having a search window. The pixel weights are computed by comparing patches in the target with the N nearest patches found from same the structure in the prior images. Formally,

$$p'_x = \frac{\sum_{y \in S_N} \exp\left(-\sum_{t \in P} \frac{|p_{x+t} - p_{y+t}|^2}{h^2}\right) \cdot p_y}{\sum_{y \in S_N} \exp\left(-\sum_{t \in P} \frac{|p_{x+t} - p_{y+t}|^2}{h^2}\right)}.$$

Here, x is the location of the target pixel and y is a similar patch in a set of nearest neighbors, S_N , for the target patch, p_x . P is the patch size. The patch similarity is measured by the L_2 distance between two patch vectors with t representing the index within a patch. The factor h controls the overall smoothness of the filtering.

In this study, we performed exact patch matching to find N similar prior patches by measuring the L_2 distance. Both this operation and the NLM filtering are GPU-accelerated.

III. RESULTS AND CONCLUSIONS

To test the localized matching of our approach we conducted an experiment with a lung CT scan (512×512, 512 images in axial-view) obtained from an online human lung database (<http://www.giveascan.org>). We randomly selected 40 images and manually labeled the right lung with a tight bounding box for the localization algorithm [2]. Two images were randomly chosen from the remaining set, one as a prior and one to generate a target low-dose CT image. For added difficulty the target image was first deformed by inflating the center radially.

This image was used to generate a low-dose CT image (720 20° fan-beam projections over 360° with 30 SNR noise added into the sinogram). The right lung of the target image was restored using the 50 nearest patches automatically found from the same organ in the prior. We quantitatively compared our method with the standard NLM (7×7 search window). In total, 49 patches were used to de-noise a pixel. Note that we used a patch size of 7×7 in this experiment. The results are illustrated in Fig. 1. We see that compared to the standard NLM filter, our method can better remove the noise while preserving more details.

We are encouraged by these initial results. It shows that we can liberate ourselves from the need for non-rigid registration methods. Registration can be error-prone and it also requires a much larger database of complete images. Conversely, by storing a database of image region-labeled patches we can remove a good amount of redundancy and in its place store more diversity. In future work, we will build a full-size patch database and test it to restore entire low dose CT images.

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