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IMAGE RECONSTRUCTION USING EQUALLY SLOPPED TOMOGRAPHIC ACQUISITION SCHEME

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ABSTRACT--We develop two new algorithms for tomographic reconstruction which incorporate the technique of equally-sloped tomography (EST) and allow for the optimized and flexible implementation of regularization schemes, such as total variation constraints, and the incorporation of arbitrary physical constraints. EST has recently been successfully applied to coherent diffraction microscopy, electron microscopy, and computed tomography for image enhancement and radiation dose reduction. However, the bottleneck of EST lies in its slow speed due to its higher computation requirements. In this paper, we formulate the EST approach as a constrained problem and subsequently transform it into a series of linear problems, which can be accurately solved by the operator splitting method. Based on these mathematical formulations, we develop two iterative algorithms for tomographic image reconstructions through EST, which incorporate Bregman and continuative regularization. Our numerical experiment results indicate that the new tomographic image reconstruction algorithms not only significantly reduce the computational time, but also improve the image quality. We anticipate that EST coupled with the novel iterative algorithms will find broad applications in X-ray tomography, electron microscopy, coherent diffraction microscopy, and other tomography fields.

I. GENERAL

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too.

Image processing basically includes the following three steps:

- Importing the image via image acquisition tools;
- Analysing and manipulating the image;
- Output in which result can be altered image or report that is based on image analysis.

There are two types of methods used for image processing namely, analogue and digital image processing. Analogue image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction.

The first class focuses on preprocessing projection data before image reconstruction. The optimization variables are projection data. Hsieh proposed an adaptive filtering approach where the filter parameterization was adjusted according to the noise property. Since the introduction of computed tomography (CT) in the 1970s, a wide-spread concern on CT is the increasing risk of cancer induced by X-ray radiation. The radiation doses delivered to patients during X-ray CT examinations are relatively high when compared to other radiological examinations [3]. Based on a recent report, the overall averaged radiation dose associated with a routine abdomen/pelvis CT scan is around 10 mSv, which is roughly 5 times of head CTs and 100 times of chest X-ray Radiography. Additionally, the dose in CT is cumulative in lifetime, and successive CT scanning can significantly increase the lifetime radiation risk of fatal cancers.

CT is also frequently used to guide the surgery or radiotherapy by providing localized contrast information between tumors, organs and other surrounding human tissues. Patients with diagnosed or suspicious abdomen tumors would be submitted to repeated CT scans over a long observing period before or after surgery or therapy. Low dose CT (LDCT) is therefore of major importance in order to alleviate the harm caused by cumulated radiations for the patients with abdomen tumors. Among all the methods proposed so far to obtain LDCT images, the most practical and widely used method is lowering the X-ray tube current by modulating the mA or mAs setting, but at a cost of degraded CT image quality due to increased quantum noise and artifacts [5-7]. In the past ten years, other approaches have been explored to improve the quality of LDCT images. They can be divided into three categories: pre-processing approaches, reconstruction approaches and post-processing approaches. The first one refers to techniques that improve the CT imaging by restoring the projected raw data before filtered-backprojection (FBP) reconstruction. Adaptive filtering, multiscale penalized weighted least-squares and bilateral filtering have been reported to suppress the excessive quantum noise in projected raw data.

Reconstruction approaches treat the LDCT imaging as an ill-posed inverse problem, and solve the problem via maximizing a prior-regularized cost function using iterative optimizations. Many prior options have been proposed in the past decade, for example the total-variation minimization the nonlocal prior reconstruction, and the prior image constrained compressed sensing (PICCS) algorithm. It should be noted that results of clinical value in abdomen LDCT have been achieved by using the PICCS algorithm and the adaptive statistical iterative reconstruction (ASIR).

However, due to the difficult access to well-formatted projection data of the main CT vendors, researches on pre-processing and reconstruction approaches are often limited in practice. Another well-known concern for iterative reconstructions is the intensive computation cost required for reconstruction, which may delay clinical workflow and diagnosis. Additionally, the CT scanners equipped in most current hospitals are based on FBP algorithms and upgrading to the latest CT scanners with iterative algorithm is often too expensive.

II. PROBLEM STATEMENT

It is well known that X-ray radiation can be harmful which may induce genetic, cancerous, and other diseases. Therefore, the radiation risk issue is receiving more and more attention. As a result, the well-known ALARA (as low as reasonably achievable) principle is applied to avoid excessive radiation dose in the medical community. Since X-ray imaging is a quantum accumulation process, the signal-to-noise ratio (SNR) depends on the X-ray dose quadratically.

Given other conditions being identical, reducing the X-ray dose will degrade image quality. Consequently, how to reconstruct adequate CT images at a minimum radiation dose level is a hot topic in the CT field. There are two strategies for radiation dose reduction: the first one is to reduce the X-ray flux towards each detector element, and the second one is to decrease the number of X-ray attenuation measurements across a whole object to be reconstructed. The former is usually implemented by adjusting the operating current, the operating potential and exposure time of an X-ray tube, leading to noisy projections. The latter necessarily produces insufficient projection data, suffering from few-view, limited- angle, interior scan, or other problems. These problems can co-exist in one dataset, representing a major opportunity for algorithmic research. To reconstruct images from noisy projections, various reconstruction algorithms were proposed. These algorithms can be categorized into two classes in terms of the variables used in the optimization process

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III. RESULT AND CONCLUSION

Based on the CS theory, the TV regularization method was widely used for CT reconstruction, and produced good results from incomplete and noisy data. Our results in Appendix have also verified that the TV regularization method can generate better results than the conventional FBP algorithm from low-dose and/or few-view datasets. However, because the TV regularization method is based on a piecewise constant image model, it may produce blocky results in practical applications when there is too much noise. Moreover, the TV constraint uniformly penalizes the image gradient, and is not capable of distinguishing structural details from noise and artifacts. These problems dampen the enthusiasm for the clinical application of the TV regularization method. While many efforts have been devoted to improving the TV based CT reconstruction the soft-threshold method was selected as an example to produce the TVSIR results in our experiments for comparison with our proposed dictionary learning based algorithms.

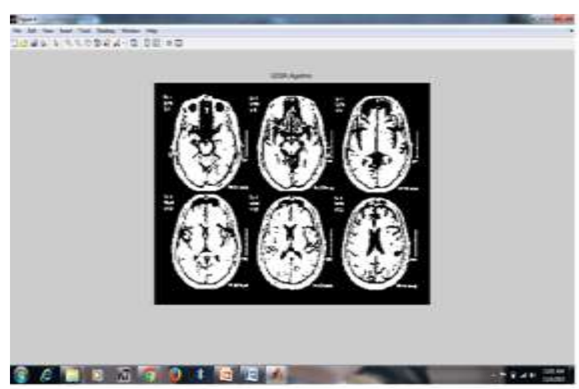

Fig 1. ADSIRAlgorithm results of Image reconstruction..

Fig 1. GDSIR Algorithm results of Image reconstruction

Different from the TV regularization method, the dictionary learning approach aims at capturing localized structural information and suppressing image noise. The sparse representation in terms of a redundant dictionary is able to keep the atoms reflecting structural features and avoid the other atoms. Use of the dictionary-based sparse representation as the regularization term for SIR is a new mechanism to improve image quality. Moreover, any missed structural information due to the enforcement of the sparsity constraint will be compensated for in the subsequent updating steps. SIR is very effective to eliminate streak artifacts, and works well with a dictionary. In principle, the dictionary learning process should lead to a sparser representation of an underlying image in a specific application.

Our simulation results for mono-energetic imaging and for one imaging region have shown that both the GDSIR and ADSIR algorithms outperformed TVSIR from low-dose and/or few-view data. However, it should be noted that there remain differences between the true image and the GDSIR and ADSIR results, as seen in Section IV-B. The basic idea of the dictionary learning based approach is to find a best match to a true image from the dictionary-spanned image space. When the true image is outside the dictionary image space, the reconstructed image can be viewed as its projection on the dictionary image space with an unavoidable error.

Therefore, some structures may be lost while artifacts may be introduced although the reconstructed results often have less noise and more structural information. A proper dictionary should represent the structural information of an object as much as possible. In this way, the reconstruction with a sparse representation in terms of the dictionary can perform well. With a global dictionary, the structural differences between its training images and a true image would affect the final reconstruction quality. Practically, both the aforementioned real data and simulation studies have demonstrated that GDSIR perform robustly well with a dictionary learned from a quite different image. Usually, it is not difficult to prepare an excellent training set with sufficiently many structural features and less noise for construction of a global dictionary. Since GDSIR does not need to update the dictionary in each iteration step, it is much faster than ADSIR. On the other hand, it is necessary to use an adaptive dictionary when a global dictionary does not match a specific application closely.

IV. EXISTING SYSTEM

Computed Tomography (CT) is a widely used medical imaging method which is employed to visualize interior organs within the human body and obtain information of their structural properties from a set of X-ray projections. Starting with its introduction in the 1970s, CT has become an essential tool in medical diagnostic and preventive medicine and its use has increased very rapidly over the last two decades due to technological advances which have made the procedure much more user-friendly to both patients and radiologists. Tomographic imaging creates three-dimensional images of object properties by processing multiple measurements from transmitted or emitted energy.

V. PROPOSED SYSTEM

Some image preprocessing techniques can be involved in the proposed algorithms. Because a predetermined dictionary is not required before the ADSIR reconstruction, and the dictionary is learned from intermediate images during the iterations, there is little image preprocessing issue. For the GDSIR reconstruction, we need to predetermine a global dictionary from a training set and keep the dictionary unchanged during the iterations. To achieve a best performance, the dictionary is generally learned from well-reconstructed images with structures similar to objects of interest.

In practice, the images for dictionary training may contain non-structured noise or structure-like artifacts such as speckle noise. For the non-structured noise, we do not need any image preprocessing because the dictionary learning process is inherently good at suppressing noise. For artifacts, an image preprocessing step is helpful to avoid unexpected atoms. In the clinical study for this paper, there are speckle noises in the TVSIR results. This kind of noise would lead to speckle-like atoms in the global dictionary, which may match speckle noise well in the sparse representation and lead to speckle noise in the GDSIR results. Since median filtering is a conventional way to remove speckle noise without losing important structures, a 3.3 median filter was used to improve the image quality for global dictionary learning.

The computational cost is a common problem for all the iterative reconstruction methods. The total cost of any iterative algorithm can be expressed as the product between the computation time for each iteration and the total iteration number. In our implementation the image updating step adopted a finite- detector-based high-accuracy area model for the forward and backward projections. If there is no requirement for high resolution, the well-known distance-driven method can be used to replace the time-consuming area model [50], which can speed up the image updating step by an order of magnitude. The OMP and dictionary learning operations take comparable time as the image updating step. Rapidly, GPU and other hardware based acceleration methods have been developed, which can be applied to our algorithms.

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