Enhancement of 3D Computed Tomography Image Reconstruction Using QR Decomposition

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Abstract : QR decomposition is a framework for the direct solution of error occurred in the linear image reconstruction problems. first analyze the structure of linear image quality parameters, conditions and cost functions to show that the obstacle to the application of QR decomposition methods to their solution is the variable mixing in the Computed Tomography (CT) model. The relation between well-known undecimated wavelet transforms, then we present new filter banks specially designed for un-decimated decompositions which have some useful properties such as being appear generally in QR-decomposition. The noising methods for labeling and de-noising problems occurring in 3D-image re-construction with simulated data show errors significantly compare with our proposed technique with QR decomposition algorithm to error rectification and continuous image reconstruction techniques compare with the Wavelet Decomposition. Experiments show that the proposed method outperforms QR decomposition techniques in challenging scenarios involving reducing 3D image reconstruction.

Keywords : Computer Tomography (CT),Image re-construction ,QR decomposition

I. INTRODUCTION

MBIR algorithms arise a large size optimization problem as well as a careful choice of an optimization function along with an iterative search of the solution in which each step involves two matrix vector products. CT reconstructions have shown that Wavelet-Decomposition Algorithm can greatly improve image quality by increasing resolution as well as reducing noise and some artifacts in image re-construction. However, high computational cost and long reconstruction times remain as a barrier to the use of Wavelet-Decomposition Algorithm in practical applications.

In this system we formulate a methodology for analytically studying the propagation of errors from dynamic projection data to avoid the 3D image re-construction. This methodology is used to study the relationships between reconstruction estimators, image degrading factors and avoid statistical noise in the 3D image reconstruction of Computed Tomography (CT) model. QR decomposition algorithm process to avoid the noise in 3D image re-construction and increase the number of elements of its reconstructed image. Increasing the number of projections, this will have an impact avoidance of inverse problem. On the other hand increasing the number of measurements present on a projection and 3D image reconstruction. In this work we present the impact of these alternatives in the reconstructed image quality with QR-Reconstruction Algorithm and Wavelet Reconstruction.

The system has several advantages

- QR Decomposition has to reduce image artifacts and noise and leads toward dose reduction in CT.
- Wavelets can be used to isolate very fine details in an image reconstruction, while very large wavelets can identify coarse details.
- It can often compress or de-noise a signal without appreciable degradation
- Low computation process and low power consumption.

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II. METHODOLOGY

System Architecture

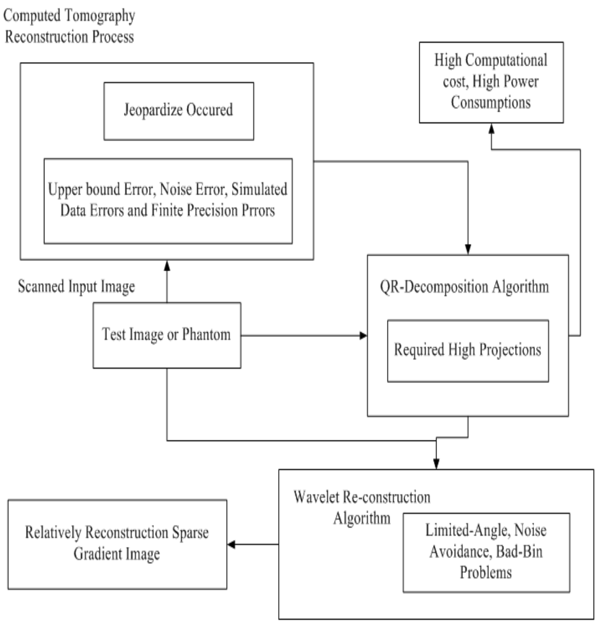

Fig 1 Schematic Diagram

Modules

1. Image Reconstruction
2. Intrusion Problem Occurred
3. Compared QR Algorithm with Wavelet Re-construction Algorithm

Image Reconstruction

As modeling the scanners, we shall define some test-images which will be used to illustrate the procedures. In tomography, a test-image is called a phantom. Physical phantoms are usually made of plastic, and may contain a number of chambers. These chambers may in turn be filled with radioactive liquid, which can be measured separately. This allows a quantitative measurement, which can be used to evaluate the accuracy of a real reconstruction. The constraints faced by an improved reconstruction method. We then show that it may also be used to create images with higher resolution at the same noise suppression, and that any reconstruction in between these two extremes can be achieved in real time by the operator.

Intrusion Problem Occurred

In practical applications of tomography imaging, there are often challenges for image reconstruction. In computed tomography (CT), image reconstruction from few views would enable rapid scanning with a reduced x-ray dose delivered to the patient. Limited-angle problems are also of practical significance in CT technique can be generalized to cone-beam CT as well as other tomography imaging modalities. A theoretical upper bound of the error, noise error, simulated data show errors and finite precision errors that will occur in there construction can be established based on the condition number of the linear system.

Compared QR Algorithm with Wavelet Re-construction Algorithm

The Wavelet Decomposition algorithm takes advantage of the benefits of the MB approach, but only requires a matrix vector product and backward substitution for the image reconstruction. Wavelet decomposition can perform image reconstructions with good quality while using a low number of projections, becoming a candidate for low dose image reconstruction. We have evaluated and demonstrated the performance of the wavelet algorithm in addressing a number of challenging reconstruction problems, including the few-view, limited-angle, noise avoidance, bad-bin problems and Low process cost. As the result the effectiveness of the Wavelet algorithm relies on the fact that the object being imaged has a relatively Reconstruction sparse gradient image.

QR- Algorithm

The most important applications of QR decomposition are adaptive beam forming, filtering applications

Forj: = 1 to n do
Begin
S: = 0;
Fori: = j to m do s: = s + a
2
ij;
S: = sqrt(s); dj: = if ajj > 0 then −s else s;

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Fak: = sqrt(s ∗ (s + abs (ajj)));

Ajj: = ajj − dj;
Fork: = j to m do akj: = akj/fak;
Fori: = j + 1 to n do
Begin
S: = 0;

Fork: = j to m do s: = s + akj ∗ aki;

Fork: = j to m do aki: = aki − akj ∗ s;

End for i;
End for j;
```

No measures have been taken to stop the computation if a column turns out to be numerically linearly dependent (fak would become zero in this case).

After this decomposition we can compute y: = QT y using the vectors wi as follows:

```
Forj: = 1 to n do (35)
Begins: = 0;

Fork: = j to m do s: = s + akj ∗ yk;

Fork: = j to m do yk: = yk + akj ∗ s;
End;
```


Fig 2 Input Image

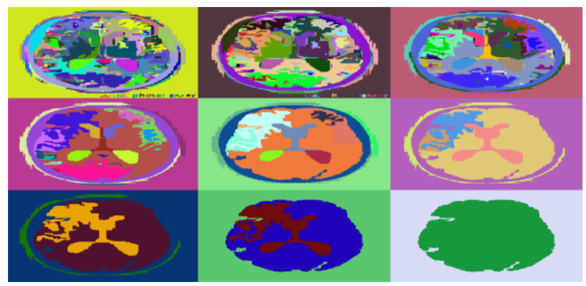
Fig 3 Output image

III. CONCLUSION

The Quality CT image reconstructions with simulated and real data are performed, image noise analysis is performed through various image quality parameters and the condition number of the linear system is related with the image quality parameters. Results show the condition number's dependence on the CT model. Image reconstructions with simulated data show errors significantly below the condition number theoretical bound and image reconstructions with real data show that quality improvements depend strongly on the condition number. This allows a reduction on the number of projections without compromising image quality and places this reconstruction method as a strong candidate for low-dose 3D CT imaging reconstruction.

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