Chapter 3

RECONSTRUCTION TECHNOLOGIES FOR MEDICAL IMAGING SYSTEMS

Advances in Algorithms and Hardware for CT

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Abstract: Medical imaging made immense advances in the last years. Beside new modalities the traditional imaging techniques and systems made rapid improvements. A good example is the improvements of Computerized Tomography (CT) with the introduction of large detector arrays. One of the important technological challenges of most medical imager is the reconstruction technology, which has to deal with complex imaging techniques and steadily increasing requirements. This chapter provides a brief insight into this field and discusses some technological aspects of reconstruction for CT.

Keywords: Reconstruction, CT, hardware acceleration

1. INTRODUCTION

Most medical imaging devices use physical interactions to generate spatially resolved maps of static properties or functional information. Sensors are used to measure an impact of these physical interactions. Only in few cases the detected signals represent the final images directly (e.g. X-Ray radiography). In most imaging devices, the detected data itself are not useful for medical diagnosis and are usually converted back to the spatially resolved physical effect in the object that causes the acquired signals. The functional chain from the physical interaction up to the detected signal is called the forward problem and is usually well understood. However, the forward problem can become very complex and can include a number of disturbing effects such as scatter radiation, noise, or imperfections of the medical imaging device. Reconstruction is the inversion of the forward

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problem. It estimates the physical interaction from the acquired data given a forward model of the measurement.

Most medical imaging devices have sensors outside the patient and detect data that do not only belong to a single point in the object but to larger areas. An example is a X-Ray beam that undergoes absorption on its way through the patient. The related mathematically forward models usually include integration in the object domain. This integral is usually the key problem of the reconstruction and requires integral transformation techniques. This can be demonstrated with simplified system models of some imaging modalities.

Computerized Tomography generate images of the X-ray absorption coefficient *$\mu(x)$* at position x using measurements of the remaining X-ray intensities I of a beam with a primary intensity of I_0 along a line S. The forward problem becomes:

$$I = I_0 e^{-\int_S ds \mu(s)}$$

A simple 2D Magnetic Resonance Tomography generates images of the electromagnetic response *m,* which is phase encoded with a gradient g_p in y direction applied for time T and frequency encoded with a readout gradient g_r in x direction. With γ being the gyro-magnetic constant, the acquired signal $s(t)$ is described in the forward model by:

$$s(t) = \int\int m(x, y)\, e^{-i\gamma(Tg_p y + tg_r x)} dxdy$$

A detector in nuclear medicine (NM) measures the integrated radiation of a line through the object that is caused by a local decay of radioisotopes. Neglecting the absorption and other effects we get:

$$d = \int a(s) ds$$

This chapter gives a brief inside into reconstruction technologies for Computerized Tomography.

2. CONE-BEAM RECONSTRUCTION IN CT

In recent years, CT scanners were subject to tremendous technological innovations. The most important improvement was the stepwise replacement of the one dimensional detection system with multi-line detectors up to two dimensional, large area detectors. These systems combine ultra-fast acquisition with high spatial resolution. The enhanced clinical value of CT created a push of CT as an important imaging modality. New important clinical application, such as perfusion studies or cardiac imaging came into reach of CT.

From a reconstruction point of view, these systems are Cone-Beam systems. The name reflects the geometrical shape of the x-ray beam, which is a serious challenge for reconstruction technologies. The related problems are twofold. One problem was the development of reconstruction methods and algorithms that produce good images, free of so-called cone-beam artifacts. The other challenge is the enormous amount of processing that came along with the complex reconstruction methods. This very practical problem is a severe burden for the industries, because the clinical workflow of CT imaging should not suffer from long reconstruction times. The use of non off-the-shelf super computer is considered as too expensive.

3. FROM 2D RECONSTRUCTION TO 3D CONE-BEAM RECONSTRUCTION

The reconstruction of CT images from a 2D scan is a well-defined mathematical problem. After some preparations of the measured data, the problem can be simplified to reconstruct a 2D function from line integrals of this function. The problem can be investigated as a mathematical problem of continuous functions, ignoring the discrete nature of quantities in a real CT scanner such as discrete detector samples or image pixel. The most often used solution is the so-called filtered back-projection, which reads

$$f(x, y) = \int_0^{2\pi} \int_{-\infty}^{\infty} p(\phi, u) h(y \cos\phi - x \sin\phi - u) du d\phi$$

with *p()* being parallel projections and with the distribution

$$h(u) = \frac{1}{2} \int_{-\infty}^{\infty} |p| e^{j2\pi pu} dp$$

which is often called ramp-filter. The inner integral is a convolution of the measured data with the ramp filter. The outer integral is called back-projection because it projects the filtered data back to the image domain.

The 2D filtered back-projection formula is an exact solution to the continuous inverse problem and can be mathematically proven. The general structure of the algorithm, filtering of the projection data and back-projection into the image domain, can also be found for similar reconstruction problems such as cone-beam reconstruction.

Similar to other analytical reconstruction methods that solve the reconstruction problem by means of an analytical reconstruction formula, this solution has to be discretized to finite sets of discrete projection angles, detector samples and image points. For the discrete representation of the data and the reconstruction, care must be taken to use proper sampling patterns and to limit the frequency band of the continuous functions.

The 2D reconstruction formula above assumes parallel ray geometry. Today's CT scanners are usually so-called third-generation scanners with an imaging system that rotates around the patient. A point-like focal spot emits an x-ray beam with a fan or cone shape, which is detected in a 1D or 2D detector array on the opposite side. The problem of the different ray geometry (divergent versus parallel) can be solved with a reformulated version of the reconstruction algorithm or by means of a so-called rebinning step that transform the fan beam data into parallel beam data.

The reconstruction of 3D cone-beam projections has a number of similarities to the 2D problem and again there exists a simple exact reconstruction formula. Unfortunately this formula requires parallel beams similar to the 2D version. Other than in the 2D case, there is no simple way to either reformulate the algorithm or to rebin the data. This was a serious challenge and it took quit some time until proper reconstruction methods became available.

Radon[20] derived a good theoretical framework of the inversion of integral transformations. This framework can directly be used for 2D reconstruction, because *Radon* described the *Radon transform,* which is equivalent to the forward problem and the *inverse Radon transform,* which is a reconstruction. The measured data i.e. the line integrals form the so-called *Radon domain*. The framework can also be applied to 3D functions. The *Radon domain* of a 3D function describes plane integrals of the function. One basic problem of the application of this framework to cone-beam reconstruction is the fact that a cone-beam scanner measures sets of line integrals and not plane integrals. However the framework of *Radon* can be used to consider some theoretical properties of reconstruction methods and it was the base of a class of exact reconstruction methods for cone-beam reconstruction.

3.1 Approximate reconstruction techniques

The absence of proper reconstruction techniques and later the high technological burden to use 3D cone-beam reconstruction techniques lead to a class of reconstruction techniques that performed some transformation or approximation of the acquired cone-beam data in such a way that the final reconstruction could be done with a traditional 2D technique. These simple solutions work fine if the number of detector rows and the related cone angle are small. For large detector arrays and large cone angles, the resulting image quality suffers from the approximation to 2D and shows so-called cone-beam artifacts. One example is the 'nutating slice algorithm'[17] or derivates[10]. This algorithm fits 2D planes to the helical trajectory. The projection data that are closest to this plane are extracted from the cone-beam data and are reconstructed with a 2D technique. Since the orientation of the 2D slices is coupled to the helix of the source trajectory, they are nutated relative to each other.

Another class of approximate algorithms generalizes the basic 2D methods into 3D. Good examples are [4,28,19]. These methods are of the type filtered back-projection. The rules for filtering in these methods are based on heuristics and geometrical considerations. However, there is no proof for exactness. The back-projection is a true 3D back-projection. A key feature of these algorithms is the utilization of the measured data. The framework of *Radon* allows the inspection of the used data in terms of completeness and redundancies, even if the inversion techniques of Radon are not applicable. For limited cone angles, these algorithms perform well and are in use in some clinical scanners. Especially the Wedge algorithm combines little cone-beam artifacts with good dose utilization and insensitivity against motion artifacts. The dose utilization measures, how good the x-ray exposure of the patient is utilized to provide images with good signal to noise ratio. Motion artifacts are image degradations from inconsistent projection data caused by patient motion during the data acquisition.

With the growing detector size in medical CT scanners, the need of helical acquisition techniques becomes less important. For some applications, the cone-beam covers the entire region of interest (40mm with state-of-the-art scanners). This could enable to use a single axial turn of the CT scanner to measure the entire region of interest. Unfortunately this attractive scan protocol has severe shortcomings. Up to now, there is only one basic reconstruction method available for this acquisition[9]. This method and its derivates generate severe artifacts, which can hardly be accepted especially in low contrast applications. Even worse, there is hardly any hope that this problem can be overcome with improved reconstruction techniques. The axial scan trajectory suffers form a so-called missing data problem. It can be shown using the framework of *Radon* or other sufficiency conditions[27,24] that not all data have been measured that are required for an exact reconstruction. It is assumed that this fundamental problem can only be overcome with other scanning trajectories that acquire all or at least more data for accurate reconstruction.

3.2 Exact reconstruction techniques

The first algorithms for exact cone-beam reconstruction[27,8,5,16] required non-truncated projection data and were not applicable for axial truncated data of helical cone-beam CT. Non-truncation in the above sense means that the entire object must be in the cone-beam. This problem was solved with the *Tam-Danielsson* window[25,3]. This window defines a detector shape with some unique features. The most important feature becomes visible if one takes an arbitrary cross section through the scanned object. Inspecting the cross sectional plane of all cones which have the focal spot in this plane, one can see that the plane is segmented into triangles that cover the entire plane completely and without any redundancy. The cross sections can be related to *Radon* planes. Each *Radon* plane is covered by a set of triangles, which are part of the measure cone-beams. Together with an important relation of plane integrals and divergent line integrals[8], it was possible to calculate the derivative of *Radon* planes from cone-beam projections. In the first algorithms based on these results, a limitation of the object support in axial direction by the entire helical scan was still required. This so-called long object problem was later solved[21,22,26]. One shortcoming for clinical applications was the restriction to a fixed pitch, defined as table feed per gantry rotation with a given detector size. This problem has been solved[19] with the *nPI* method that allows a set of discrete pitches.

A breakthrough was achieved with the work of Katsevich[11,12,13]. The basic achievements of Katsevich were later generalized and applied to other reconstruction problems, such as the 3PI acquisition[1,14], or the general nPI acquisition[2]. These methods are filtered back-projection methods, were the filtering direction has to be chosen such, that the *Radon* domain is captured completely and without any redundancy. The framework is very general and can be applied to reconstruction problems, if a proper set of filter directions can be found.

Sidky[23] recently achieved another important exact reconstruction technique with the exchange of the integration order. This novel reconstruction technique performs the back-projection prior to the filtering, which takes now place in the image domain. An important feature was added by Pack[18] and allows the utilization of arbitrary amount of redundant data.

Exact reconstruction methods are currently not used in commercial medical CT scanner although cone-beam artifacts become more important for large detector arrays. A basic shortcoming of these methods is the problem to handle redundant data properly. Redundant data are acquired if the physical detector is larger than required by the Tam-Danielsson window or by consideration to fill the *Radon* domain completely. These redundant data should properly be used to achieve a high x-ray dose utility. Even more important, this data are essential for the reduction of motion artifacts. Recent results[15] that aim to overcome this limitation and combine the absence of cone-beam artifacts from the exact methods with the relative insensitivity to motion artifacts of approximate methods look promising. However, exact reconstruction methods have to demonstrate robustness and practicality.

3.3 Iterative reconstruction techniques

A very different class of reconstruction techniques is called iterative reconstruction. Instead of searching for an analytical solution of a continuous problem, the basic approach of these techniques is to model the imaging process with a discrete system model. A discrete set of image points μ and measurements p are linked with a system matrix A to a simple linear model:

$$p = A\mu$$

The system Matrix A basically describes the system geometry and models how much an image point influences a measurement sample. It can become more complex and take other system aspects of the forward problem into account. Within this model, the reconstruction problem becomes to estimate μ from a measurement p. Several numerical methods exist to solve this problem, typically with an iterative algorithm. From a mathematical point of view, the equation system is usually over determined and inconsistent, because there are more projection samples than image points and the data are inconsistent due to noise.

A powerful method to solve such a problem is ART[7]. ART takes an intermediate image μ^n and applies the forward system matrix to obtain a part of the projection data p^n. A proper part could be a set of parallel rays through the image. These calculated projections are compared to the measured projections p and the difference is used to update the intermediate image. A simplified version of ART is:

$$p^n = A\mu^n$$
$$\mu^{n+1} = \mu^n + \lambda A^T(p - p^n)$$

This process is repeated e.g. with other projection parts, until a stopping criteria is meet. The parameter λ is to control the convergence speed.

Even more powerful techniques take the noise in the measured data into account. A very popular method is the Maximum Likelihood (ML) method. Each projection value is modeled, as a random variable were the measured value is the expected value and the probability distribution is known. A simple noise model is to assume Poisson statistics of the measured data. Given an intermediate image μ, we can calculate the projections p of it. Knowing the probability distribution of each projection value, we can calculate the likelihood of the intermediate image for one projection value or the total likelihood as the product of the individual likelihoods. In other words we can calculate the likelihood $L(\mu)$ of an image, given a set of projections and a noise model. With some iterative numerical methods, we can search for an image that has the highest likelihood. Statistical reconstruction is a science for itself and far beyond the scope of this book. However the simple introduction can help to better understand the features of this reconstruction technique.

ML reconstruction methods have a significantly better signal to noise ratio (SNR) than analytical methods. This is due to the incorporation of a proper noise model. ML reconstruction techniques are widely used in nuclear medicine (NM), were the count rates are typically low and the SNR advantage of ML is essential. Fessler[6] showed that the advantage can also be realized in transmission scans such as CT. SNR improvements between 1.4 and 2 have been reported[29]. This advantage could be used to reduce the x-ray dose by a factor of 2 to 4 and still provide the same SNR as conventional reconstruction methods. Studies with clinical data demonstrated that the image quality is better or equal to standard reconstruction methods. Although the advantages are known, iterative reconstruction methods are not applied in commercial CT scanner due to the enormous amount of processing power required for the reconstruction. The processing time of statistical reconstruction methods is acceptable for NM due to two reasons:

- The processing time depend on the number of image points and the number of detector channel. These numbers are typically low compared to CT (typical number of image points per plane NM 64x64 versus CT 512x512).
- One acquisition in NM lasts typically 15 to 30 min. If a reconstruction takes about as long as the acquisition, the workflow does not suffer to much.

This situation is very different for CT. Unfortunately the number of image points has to be increased compared to an analytical reconstruction technique. To achieve the good results, the entire imaging area has to be reconstructed on a fine grid. This is because the discretization in the image domain goes already into the system model and influences the behavior of the algorithm. The resulting processing time for typical parameter settings and off-the-shelf computer hardware varies between hours and weeks and is not acceptable for clinical use.

However it is expected, that the constantly increasing performance of computer hardware and especially some dedicated computer systems will sooner or later overcome this restriction, and will make the potential dose saving and the other advantages of statistical reconstruction methods available for the clinical use.

As mentioned earlier, iterative techniques allow to integrate more imaging system aspects as just the basic geometry and physics.

4. HARDWARE ACCELERATION

The reconstruction process of a typical CT system consists of four major parts:

- Raw data correction.
- Data rebinning.
- Filtering.
- Back-projection.

The raw data correction is required to compensate for a number of effects on the measured data. The correction algorithms are usually not very computational intensive and can be realized with off-the-shelf computer systems.

The filtering and the final back-projection are sometimes done in a geometry that differs from the geometry of the CT system itself. This transformation is often called rebinning. One example is the transformation of fan beam data to a parallel geometry. The processing consists of some interpolation steps without high demands on the processing power.

Step number three, the filtering is usually be done in the *Fourier* domain. The processing includes a (Fast) Fourier transform, a multiplication with the filter and an inverse (Fast) Fourier transform. The analysis of the computational effort shows that the required processing power is equivalent to about one state-of-the-art personal computer. The main processing load comes from the Fourier transforms. For costs reasons, a more efficient implementation using off-the-shelf Digital Signal Processor (DSP) accelerator or FGPA based sub-systems can be considered.

The back-projection is much more demanding than the previous processing steps and requires special attention. In the following, an estimate of the computational effort is provided. The estimations are not very precise, because they depend on a number of details. The speed of different implementation can easily vary by a factor of two or more. However they can be used to get an impression of the order of magnitude of the problem.

Back-projection is a simple operation that has to be performed very often. The basic operation is to take one image point, calculate the projection of this point onto one projection, perform an interpolation of the projection and add the result to the image point. In a simple 2D case, this operation requires roughly 20 instructions of a standard processor. The operation has to be repeated $2.5x10^8$ times for a 512x512 image slice back projected from 1024 projections. Today's (2005) standard processor can perform this operation with a rate of about 2 images per second. In the 90's, this was a real challenge for the first spiral CT scanners that were able to scan about 1 slice per second. The *easily* available processing power was a few hundred times less. At that time, Philips Medical Systems (PMS) managed this problem with a dedicated processor, which was highly optimized for this operation. Two main architectural choices made it possible to achieve a performance level of about 400 times the performance of off-the-shelf workstation computer systems. The first was to parallelize the operations. Instead of performing the 20 instructions in sequence, a dedicated computational pipeline was able to perform one complete back-projection operation in a single cycle. The second choice was to use multiple units and build a multi-processor system with 14 units. The high specialization of the processor made it possible to increase the operation frequency. All measures together, enabled PMS to build a cost effective accelerator board that reaches real time performance, with a system that could reconstruct two images per second. The price of this attractive reconstruction unit was an investment in processor architecture and design.

The next challenge came with the introduction of cone-beam CT systems. In the beginning of the millennium, the CT systems required:

- Cone-beam reconstruction algorithm without cone-beam artifacts.
- Detector arrays with 16 rows.
- Faster rotation time (0.5 sec).

The effective acquisition speed has increased by a factor of about 30. This was already a serious challenge and some CT manufacturer decided to stay with 2D reconstruction techniques. The 3D cone-beam reconstruction algorithm required about 20 to 30 times more processing power for a basic back-projection operation than the 2D equivalent. An additional problem was that the traditional 2D hardware acceleration systems were not able to perform these more complex 3D operations. Again PMS took the challenge and designed a dedicated 3D cone-beam processor with the latest available semiconductor technology. The result was about the same. It was possible to improve the processing speed by a factor of a few hundred to thousand with dedicated hardware compared to multi-purpose computer systems.

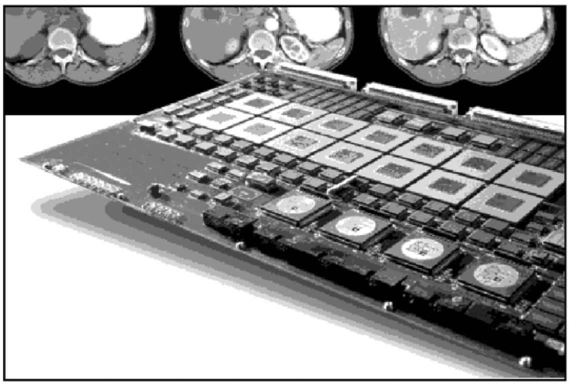

Figure 3-1. The 2D CT Reconstruction accelerator

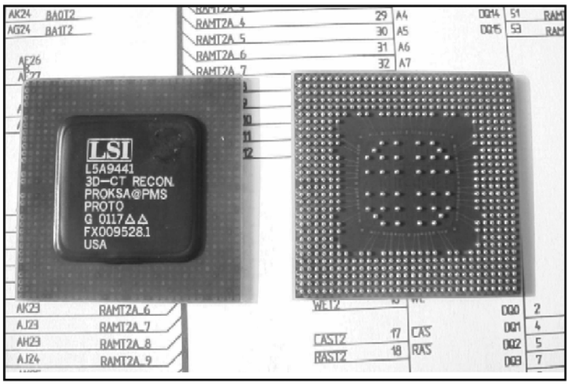

Figure 3-2. The 2nd Generation 3D Cone-Beam Processor

The actual challenges for CT reconstruction are still growing with technological improvements of the CT scanners. They are driven by faster gantry rotation, larger detector arrays (64 rows and more?), the need to use exact reconstruction algorithm or the *wish* to make use of statistical reconstruction methods.

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