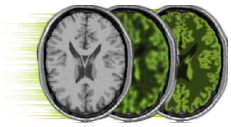
NiftyRec 1.6
Software Guide

May 21, 2012



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Chapter 1

Introduction

1.1 Overview

NiftyRec provides routines for Emission and Transmission Tomographic reconstruction. The software is written in C and computationally intensive functions have a GPU accelerated version based on NVidia CUDA. NiftyRec includes a mex-based Matlab Toolbox and a Python module that provide easy to the low level routines for reconstruction, hiding the complexity of C and of the GPU accelerated algorithms, while maintaining the full speed. Fast projection and backprojection with depth-dependent collimator and detector response and attenuation correction are at the core of NiftyRec. NiftyRec has been designed for performance, ease of use, modularity, accessibility of the code and portability.

1.2 Feature List

Projector and Backprojector

- Depth-dependent Point Spread Function (DDPSF)
- Attenuation correction
- Rotation based ray-tracing
- FFT based convolution
- GPU acceleration

Reconstruction algorithms

- Maximum Likelihood Expectation Maximization (MLEM)

- Ordered Subsets Exectation Maximization (OSEM)
- One-step-late Maximum a-posteriori Expectation Maximization (OSL-MAPEM)
- Gradient ascent Maximum Likelihood and Maximum a-posteriori

Priors

- Total variation
- Joint Entropy based anatomical prior

Scatter Correction

- Reconstruction Based Scatter Correction (RBSC)

Bindings

- Matlab
- Python

Miscellaneous functions

- Generate 3D synthetic phantoms
- Load and write DICOM and NIFTY files
- GPU accelerated 3D affine transformation

1.3 Algorithms for Emission Tomography

1.3.1 Projection and Backprojection

Iterative reconstruction methods based on a stochastic model of the emission process [**?**, **?**, **?**] have been widely shown to provide better image quality than analytic reconstruction [**?**, **?**]. The reason for the improvement in image quality is that photon count statistics are taken in account in the model of the imaging system; furthermore stochastic methods facilitate the inclusion of complex system models that take into account detailed collimator and detector response (CDR).
The CDR, including collimator geometry, septal penetration and detector response, may be taken into account in a stochastic reconstruction algorithm in the form of a Point Spread Function (PSF) that modulates the response of an ideal Gamma Camera [**?**][**?**].

The computational complexity associated with stochastic reconstruction methods however still limits their application for clinical use and inclusion of complex system models further increases the computational demand. Projection and backprojection constitute the most burdensome part of a reconstruction algorithm in terms of computational resources and memory and are performed recursively at each iteration step.

Efficient computation of line integrals for projection and backprojection by ray-tracing was proposed by Siddon [**?**]. However with a ray-based approach it becomes inefficient to include a depth-dependent PSF, as this requires the casting of a number of rays within a *tube of response* for PET [**?**] and a *cone of response* for SPECT [**?**]. Furthermore, though there exist GPGPU accelerated implementations [**?**], ray-based projectors cannot fully exploit Single Instruction Multiple Data (SIMD) architectures such as GPGPUs because of sparsity of data representation and low arithmetic intensity due to independence of the rays.

NiftyRec is based on an implementation of the rotation-based projection and backprojection algorithm proposed by Zeng and Gullberg [**?**]. This algorithm drastically reduces memory requirements and allows to perform convolution with the PSF in the frequency domain in $O(N\ logN)$ by means of Fast Fourier Transform.
Rotation-based projection and backprojection are particularly well suited to GPGPU acceleration because reorganization of the data into a regular grid yields efficient use of the *shared* memory and of the global memory bandwidth provided by the GPU architecture. Moreover the algorithm takes advantage of the hardware based trilinear re-sampling, offered by the GPU's 3-D texture memory fetch units.

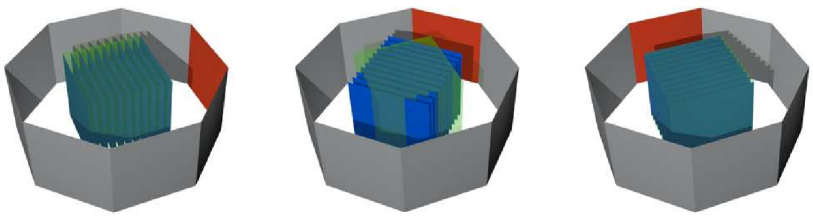


Figure 1.1: Rotation-based projection: the activity is re-sampled on a regular grid aligned with a camera and then projected. This enables FFT based convolution with the (depth-dependent) collimator-detector response.

Let the radio-pharmaceutical activity within the region of interest of the

patient's body be a continuous function denoted by $\tilde{y}$. In order to readily discretize the reconstruction algorithm, it is convenient to imagine that the activity is in first place discrete in space [**?**]. Let us approximate $\tilde{y}$ by a set of point sources $y = y_b, b = 1, .., N_b$ displaced on a regular grid.
As each point source emits radiation at an average rate y_b proportional to the local density of radio-tracer and emission events in a same voxel are not time correlated, the number of emissions in the unit time is a Poisson distribution of expected value y_b. The geometry of the system and attenuation in the patient determine the probability p_{bd} that a photon emitted in b is detected at detector pixel d. From the sum property of the Poisson distribution, the photon count in d has Poisson *pdf* with expected value $\sum_b p_{bd} y_b$. Given activity y, the probability to observe counts z is

$$p(z|y) = \prod_{d=1}^{N_d} \mathcal{P}(\sum_b p_{bd} y_b, z_d) \tag{1.1}$$

Amongst all the activity configurations that might have generated the observed photons, the activity that maximizes the *likelihood* function is optimal in the sense of the L2 norm of the difference from the true value, for the log linear distribution $p(z|y)$ [**?**].

$$\hat{y} = \arg\max_y \ p(z|y) = \arg\max_y \ \log p(z|y) \tag{1.2}$$

Expanding $log\ p(z|y)$:

$$\hat{y} = \arg\max_y \ \sum_{d=1}^{N_d} \left(\sum_b p_{bd} y_b + z_d \log \sum_b p_{bd} y_b \right) \tag{1.3}$$

A gradient-based optimization algorithm, such as gradient ascent, requires the gradient of the likelihood function with respect of the activity in each point source, differentiating the log of 1.1:

$$\frac{\partial \log p(z|y)}{\partial y_r}|_{y=\bar{y}} = \sum_{d=1} p_{bd} + \sum_{d=1} p_{bd} \frac{z_d}{\sum_{b'} p_{b'd}\ y_{b'}}|_{y=\bar{y}} \tag{1.4}$$

$\sum_{b'} p_{b'd}\ y_{b'}$ is referred to as projector, and $\sum_d p_{bd} f_d$ as backprojector of f_d.
Similarly the Expectation Maximization algorithm for maximization of the *likelihood* (MLEM) implies projection and backprojection [**?**]:

$$\hat{y}_b^{(k+1)} = \hat{y}_b^{(k)} \frac{1}{\sum_d p_{bd}} \sum_d p_{bd} \frac{z_d}{\sum_{b'} p_{b'd}\ \hat{y}_{b'}^{(k)}} \tag{1.5}$$

In case of ideal CDR, with a parallel hole collimator, the system matrix p_{bd} is non-zero only along lines perpendicular to the collimator entry surface and the projection is a line integral operator. A more detailed system model accounts for the sensitivity of each detector pixel to radiation emissions from each voxel. With a planar detector, coupled to a parallel hole, cone beam or fan beam collimator, the sensitivity is invariant to shift along the detector plane. With shift invariant CDR, projection is factorisable into a line integral operator and a convolution operator [**?**]. The CDR is generally dependent upon the distance from the detector plane.

The rotation-based projection and backprojection algorithm proposed by Zeng and Gullberg [**?**] was adopted as it suits the GPU architecture and is convenient to be incorporated with depth-dependent response functions. For each position of the gamma camera, the image matrix volume is rotated so that the front face of the volume faces the detection plane - Figure 1.1. As the image is re-interpolated on a grid that is aligned with the detection plane, all the point sources that lay on a same plane parallel to the detector are now at the same distance from the detector. A depth-dependent PSF that models the CDR can be incorporated efficiently by convolving each parallel plane with the PSF that models the relative to the distance of the plane from the collimator. The convolution can be performed by multiplication in the frequency domain, reducing the complexity from $O(N^2)$ to $O(N\ logN)$. Backprojection similarly takes advantage of rotation to incorporate the depth dependent PSF. Details of the implementation of the projector and backprojector are given in the next section.

1.3.2 GPU acceleration

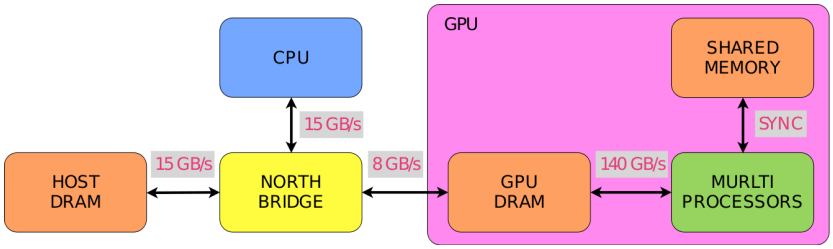


Figure 1.2: Memory structure of the host machine and GPU and typical memory bandwidth.

For problems that present enough task parallelism, state of the art GPUs can provide an acceleration of up to 10x over a high end CPU, however the

speedup can increase by another order of magnitude if the structure of the algorithm allows for efficient use of the *shared memory* of the GPU [**?**, **?**, **?**]. While on CPUs the cache hierarchy compensates costly accesses to external RAM and cache heuristics account for a large class of computational problems, the simplified memory hierarchy of GPUs requires careful design of the algorithms for efficient memory access. The external memory is directly exposed to the programmer, who has to consider explicitly coalesced access due to the mismatch between data rate and cycle time of the DDR memory. On the other hand the simpler structure of the memory and vicinity of the RAM to the processor yield data throughput 10 times higher than the throughput between CPU and RAM - Figure 1.2.

The fast RAM memory of the GPUs explains the 10× speedup, however the Single Instruction Multiple Data (SIMD) architecture and the *shared memory* of the GPU provide additional speedup for a class of computational problems. In the SIMD architecture, many processor cores fit on the same chip due to simplified design of the processor cores, which are grouped, in the case of NVidia GPUs, in a *multiprocessor* with a single common fetch unit. Multiple cores can operate concurrently in a *multiprocessor* if they execute the same instruction, so if the computational problem is such that the same operation is performed on multiple segments of data, the GPU can use a great number of processors at the same time. As the RAM data throughput would still be too low to continuously feed data to all the cores, the processor cores that are grouped in a *multiprocessor* have access to an on-chip memory that can be read and written concurrently by all the cores in a single clock cycle, through multiple data paths. The size of the *shared memory* is limited to a few Kbytes on currently available GPUs. This design offers the possibility to exploit the full power of the cores as long as the cores in a multiprocessor can reuse the data that resides in the *shared memory*, hiding accesses to the global memory, that is hundreds of times slower. In order to take full advantage of the GPU architecture, a computational problem needs to expose parallel tasks that run on each multiprocessor, each task being partition-able into serial tasks that use limited memory (up to a few Kbytes) and present a high ratio between the number of operations and the accesses to memory.

Another feature offered by Nvidia GPUs is hardware trilinear interpolation. A portion of memory may be specified as a 1D, 2D or 3D array and floating point memory addresses are accepted by the memory access unit, which decodes the non-integer address, reads the values stored in the nearest memory locations and interpolates linearly.

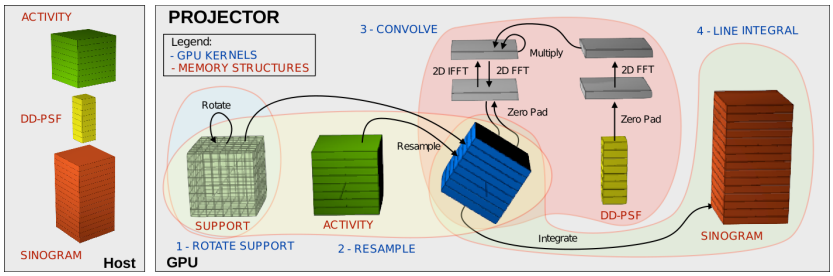


Figure 1.3: Rotation-based projection on GPU

Ray-tracing on GPU can take advantage of the fast RAM memory of the GPU and of hardware interpolation, however independence of the rays impedes efficient use of the *shared memory*. It might be possible to take advantage of the shared memory as the rays share some information, however that would imply processing concurrently multiple partial rays in blocks in a way that exposes the data in common. Rotation-based projection and backprojection reorganize data in a way that exposes the data locality.

Projector

Activity and the depth dependent PSF are copied to the GPU global memory and additional memory is allocated for the sinogram and for each of the structures depicted in Figure 1.3. The support of the image (ordered list of the x, y, z indexes of the image voxels) is extracted and stored in global memory.

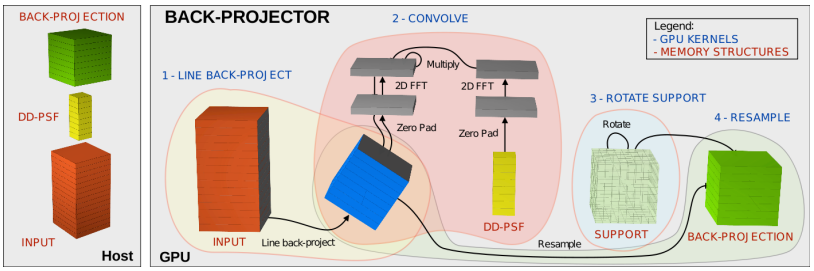


Figure 1.4: Rotation-based backprojection on GPU

For each position of the gamma camera, the activity matrix volume is rotated so that the front face of the volume faces the detection plane. In order

to optimize the usage of the GPU, rotation is performed by multiplying the support of the image by the rotation matrix, then the image is re-sampled at the locations specified by the rotated support. Rotation of the support maximizes the *device occupancy* (concurrent usage of the multiprocessors) and takes advantage of the *shared memory* by partitioning the matrix multiplication [**?**]. The trilinear interpolation is performed in hardware by the *texture fetch* unit of the GPU at the cost of a memory access and coalesced memory accesses are obtained by partitioning the memory transfers in blocks.

For each camera's position, the activity is rotated from its initial position, rather than from the previous camera's position, in order to minimize interpolation errors. After reinterpolation, each image plane parallel to the camera is convolved with the PSF. Convolution is performed by zero-padding the plane to double its linear size, computing its 2D FFT, multiplying by the FFT of the zero-padded PSF, back-transforming and truncating. As depicted by the arrows in Figure 1.3, the convolution is performed in place, in order to minimize memory occupancy. 2D FFT is performed by means of the CUDA CUFFT library that takes into account all the architectural factors and constraints of CUDA, memory coalesced access, bank conflicts and efficient shared memory usage.

Finally a kernel sums all planes and stores the result in the sinogram data structure. Shared memory cannot be used in the summation step as the number of operations (sums) is exactly equal to the number of memory accesses, however *device occupancy* and memory coalescing are optimized by partitioning the sums in blocks.

Backrojector

The sinogram and the PSF are transfered from the host machine RAM to the GPU global memory and all the structures depicted in Figure 1.4 are allocated on the GPU memory. Two volumes are allocated for the backprojection, a rotating volume and a fixed volume that is initialized to 0 and contains in the end the result of the backprojection.

One projection at a time is extracted from the sinogram data structure and the value on each pixel is backprojected to the rotating volume along lines perpendicular to the detection plane. This step is performed by a GPU *kernel* that copies a pixel to a local *register* and then copies it back into all

the voxels in the same column of the rotating volume. Each plane of the rotating volume is then convolved in place with the PSF by multiplication in the frequency domain. The rotating volume is rotated to the zero position and then accumulated into the fixed volume.

The same series of operations is repeated for each camera's position.

1.3.3 Reconstruction Algorithms

On top of the projection and backprojection routines, NiftyRec implements a number of reconstruction algorithms. Let the radio-pharmaceutical activity within the region of interest of the patient's body be denoted by y_b with $b = 1, .., N_b$ and the number of counts in a detector bin be denoted by n_d, with $d = 1, .., N_d$. The probability that a photon emitted in b is detected in d is denoted by p_{bd}.

MLEM

Maximum Likelihood Expectation Maximization [**?**].

$$\hat{y}_b^{(k+1)} = \hat{y}_b^{(k)} \frac{1}{\sum_d p_{bd}} \sum_d p_{bd} \frac{z_d}{\sum_{b'} p_{b'd}\ \hat{y}_{b'}^{(k)}} \tag{1.6}$$

where k is the itaration number. Unconstrained MLEM suffers from dimensional instability: after a certain number of iterations the noise starts to diverge; for this reason typically the algorithm is stopped after a given number of iterations. Maximum a-posteriori reconstruction algorithms can converge to a global maximum and thus can easily adopt stopping criteria based on relative error of the image estimate.

OSEM

Ordered Subsets Expectation Maximization [**?**]: projection data is divided into an ordered sequence of subsets. An iteration of OSEM is defined as a single pass through all the subsets, in each subset using the current estimate to initialize application of EM with that data subset. In SPECT the OSEM algorithm can provide more than an order of magnitude acceleration over MLEM, maintaining similar image characteristics. While any subset of the projection space may be considered, here by subset we intend a subset of the projection angles.

$$\hat{y}_b^{(k)}(i+1) = \hat{y}_b^{(k)}(i) \frac{1}{\sum_{d \in S(i)} p_{bd}} \sum_{d \in S(i)} p_{bd} \frac{z_d}{\sum_{b'} p_{b'd}\ \hat{y}_{b'}^{(k)}(i)} \tag{1.7}$$

where $\hat{y}_b^{(k)}(i+1)$ represents the updated iterand after processing subset i, $S(i)$ contains the projection angles of subset i and k represents the iteration number.

OSL-MAPEM

Maximum a-posteriori Expectation Maximization does not generally have a closed form solution, however the One Step Late (OSL) algorithm introduced by Green [**?**] can be adopted with any prior that is differentiable once with respect to the activity in each voxel b.

$$\hat{y}_b^{(k+1)} = \hat{y}_b^{(k)} \frac{1}{\sum_d p_{bd} - \frac{\partial p(y)}{\partial y_b}|_{y=\hat{y}^{(k)}}} \sum_d p_{bd} \frac{z_d}{\sum_{b'} p_{b'd}\ \hat{y}_{b'}^{(k)}} \tag{1.8}$$

where $p(y)$ is the prior probability of activity y. The Matlab Toolbox of NiftyRec has a few examples of activity priors, such as Total Variation and priors based on a coregistered intra-subject anatomical image. Please refer to the inline Matlab documentation.

Gradient Ascent

NiftyRec implements a simple gradient ascent algorithm for optimization of the log likelihood and log posterior for maximum a-posteriori estimation of the activity.

$$\log p(y|z)\ \alpha\ \log p(z|y) + \log p(y) \tag{1.9}$$

$$\hat{y}^{(k+1)} = \hat{y}^{(k)} + \beta \left(\frac{\partial \log p(z|y)}{\partial y_r}|_{y=\hat{y}^{(k)}} + \frac{\partial \log p(y)}{\partial y_r}|_{y=\hat{y}^{(k)}} \right) \tag{1.10}$$

$$\frac{\partial \log p(z|y)}{\partial y_r}|_{y=\bar{y}} = \sum_{d=1} p_{bd} + \sum_{d=1} p_{bd} \frac{z_d}{\sum_{b'} p_{b'd}\ \hat{y}_{b'}^{(k)}} \tag{1.11}$$

The Matlab Toolbox of NiftyRec has a few examples of activity priors, such as Total Variation and priors based on a coregistered intra-subject anatomical image. Please refer to the inline Matlab documentation.

Scatter correction

NiftyRec implements the Reconstruction Based Scatter Compenstation (RBSC) algorithm for scatter compensation [**?**].

$$\hat{y}_b^{(k+1)} = \hat{y}_b^{(k)} \frac{1}{\sum_d p_{bd}} \sum_d p_{bd} \frac{z_d}{\sum_{b'} p_{b'd}\ \hat{y}_{b'}^{(k)} + \hat{n}_d{}^{SC}} \tag{1.12}$$

1.4 Algorithms for Transmission Tomography

1.4.1 Projection

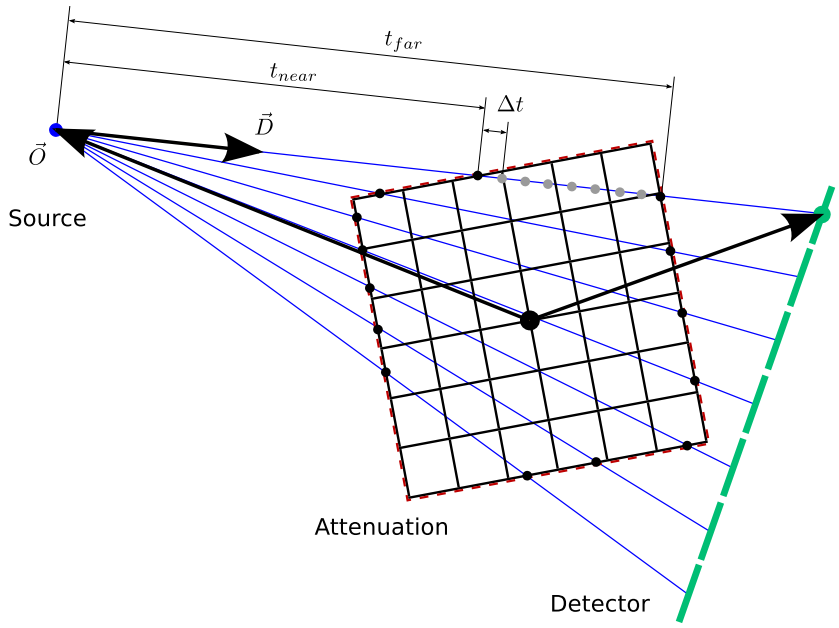


Figure 1.5:

The GPU accelerated projection algorithm is inspired on the volume render example included in the CUDA SDK 2.3. The attenuation map is defined on a 3D grid of size (N_x, N_y, N_z) voxels. Each GPU thread computes one ray from the light source to a detector pixel, accumulates the absorption coefficient along the ray and stores the result in the corresponding pixel of the 2D detector matrix. Attenuation is stored as a 3D CUDA array and is accessed by means of the the CUDA Texture Fetch Unit in order to exploit the cache system of the GPU and the hardware trilinear interpolation feature.
The algorithm scales for any size of the detector and of the attenuation map

by launching a variable number of blocks of (16×16) threads, in order to cover all the detector pixels. The bigger the attenuation map volume, the longer each threads needs to iterate (not all threads perform the same amount of operations, some terminate earlier). The position of the source is the same for all threads and is stored in constant memory; given detector size in number of pixels $(imageW, imageH)$, each thread computes its coordinate in a reference normalized plane:

```
uint x = blockIdx.x*blockDim.x + threadIdx.x;
uint y = blockIdx.y*blockDim.y + threadIdx.y;
if ((x >= imageW) || (y >= imageH)) return;

//u and v are in normalized detector pixel [-1,-1]->[1,1]
float u = (x / (float) imageW)*2.0f-1.0f;
float v = (y / (float) imageH)*2.0f-1.0f;
```

Then each thread computes the position of the detector pixel by multiplying its position in the reference plane by the (4×4) transformation matrix that represents the position of the detector with respect of the reference plane $(c_invViewMatrix)$. Finally the thread computes the unit vector $\vec{D}$ that points from the source to the detector pixel:

```
Ray eyeRay;
eyeRay.o = source;
eyeRay.d = normalize(make_float3(mul(c_invViewMatrix,
                     make_float4(u,v,-1.0f,1.0f)))-eyeRay.o);
```

The attenuation map is defined between $(-1,-1,-1)$ and $(1,1,1)$. Each thread computes the intersection with the attenuation map bounding box in order to accumulate attenuation only where it is defined. The ray-box intersection is based on the method of "slabs" implemented in the Volume Rebderer in the CUDA SDK and explained in `http://www.siggraph.org/education/materials/HyperGraph/raytrace/rtinter3.htm`. If the ray does not intersect the box then the thread terminates, otherwise it loads from texture memory the attenuation at distance t_near (see figure 1.5) from the source along direction $\vec{D}$ and iteratively loads attenuation moving at constant steps Δt until the end of the box is reached:

```
float  sum;
float  t = tnear;
float3 pos = eyeRay.o + eyeRay.d*tnear;
float3 step = eyeRay.d*tstep;

for(int i=0; i<maxSteps; i++) {
    float sample = tex3D(tex, pos.x*0.5f+0.5f, pos.y*0.5f+0.5f,
```

```
                                                    pos.z*0.5f+0.5f);

    sum = sum + sample;
    t += tstep;
    if (t > tfar) break;

    pos += step;
```

Finally the thread writes the result back in global memory and terminates:

```
d_output[y*imageW + x] = sum;
```

Chapter 2

Developer's Guide

2.1 Getting Started

The Developer's Guide is intended for those who want to extend the functionality of NiftiRec; it explains the algorithms that NiftyRec implements, outlines the structure of the code and explains how to extend it. Please refer to the User's Guide in order to use NiftyRec through the C API or the Python or Matlab interfaces. In this case you will not need to understand all the bits and pieces of NiftyRec.

In order to embed NiftyRec functionalities within third party applications or to cerate custom applications that make use of NiftyRec through its C API, it is not necessary to build NiftyRec from the source if a Packaged Release 3.1.1 is available for the architecture and operating system of your machine. In this case, you might want to simply link against the NiftiRec compiled libraries. All the NiftiRec libraries and header files are installed by the self installer of the Packaged Release. A CMake FindPackage module is provided 2.2.1 in order to find automatically the headers and libraries with CMake.

If you intend to extend NiftiRec then you will have to compile it from source. Compilation is based on the cross-platform build-system CMake.

2.1.1 Compile with CMake

NiftyRec is based on the CMake cross-platform build-system. Compilation of NiftyRec with CMake generates all the libraries, the binary executable files and the documentation, and optionally creates a self-installing package

for your platform for distribution of NiftyRec binaries. The self-installing package will install all the libraries, the binary executables, the documentation, the development file headers and the Matlab and Python toolboxes. Self-installers for some of the most common platforms can be downloaded from `http://niftk.sourceforge.com`. In order to extend the functionality of NiftyRec it is necessary to download its source and compile with CMake.

Linux Debian

Install ccmake or cmake-gui. Under Debian Linux install from repositories:

..$ sudo apt-get install cmake-gui

Download and uncompress NiftyRec source. cd to the project main directory, create here a folder 'build', cd to that folder and run cmake:

..$ mkdir build
..$ cd build
..$ cmake-gui ..

Select options, set the BUILD_TYPE to Release or to Debug and set all the required paths for additional dependencies if you selected any of the options. Configure and Generate. Now quit ccmake/cmake-gui and build

..$ make build

In order to create an installation package with CPack run make with option 'package'

..$ make package

In order to install NiftyRec in the system run make with option 'install'

..$ sudo make install

or install the package created with 'make package'.

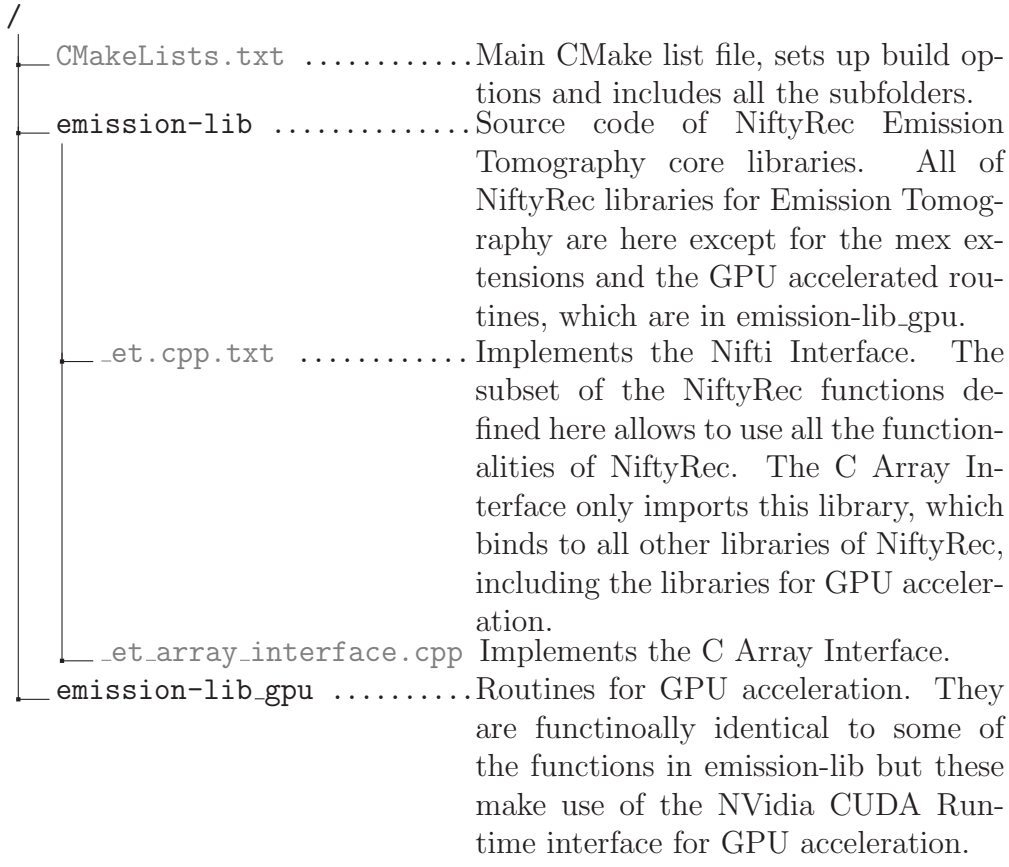
Windows

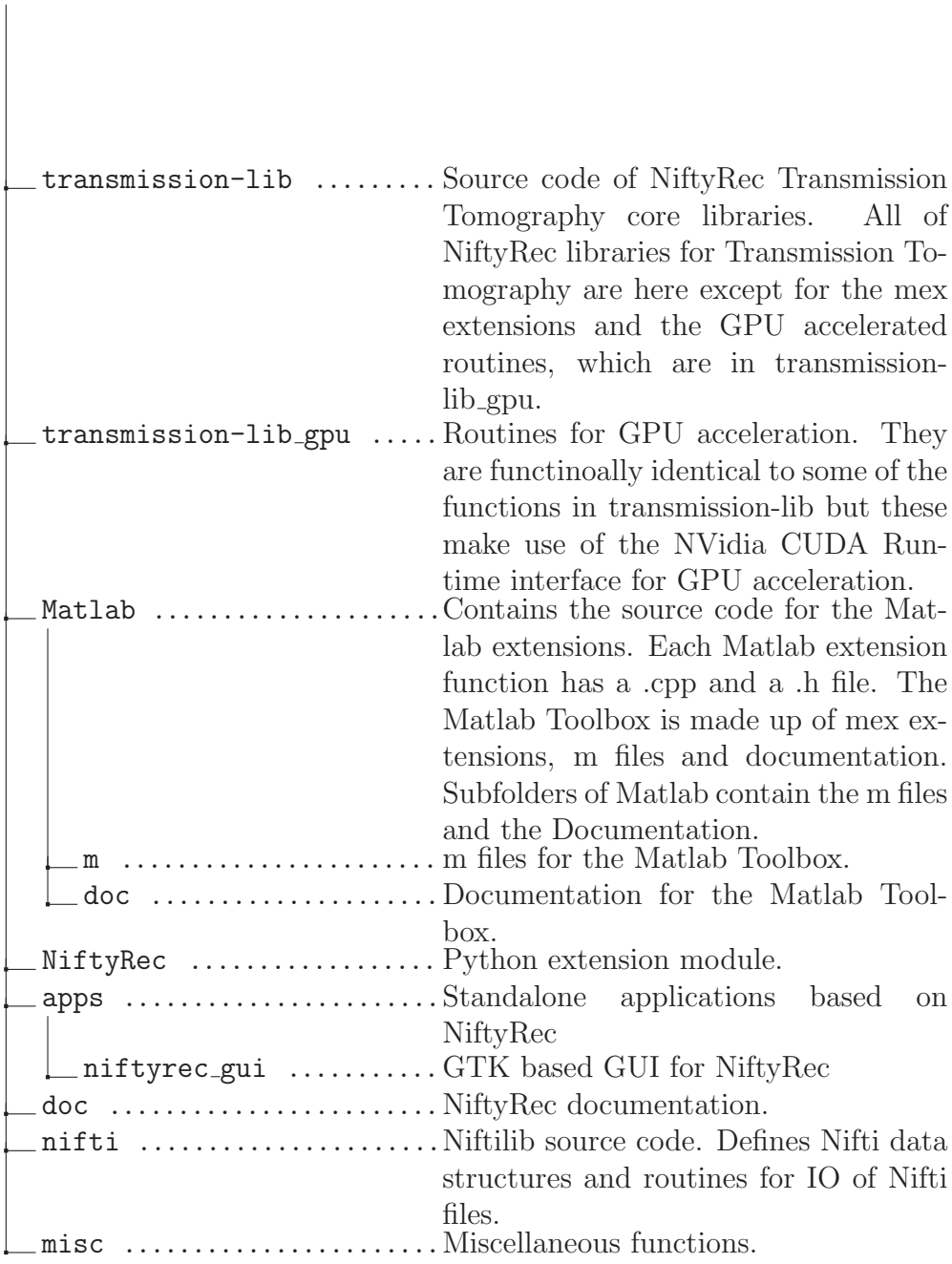
Install cmake. Download and uncompress source. Open the source directory with Windows Explorer and create here a new folder 'build'. Launch

CMake and open CMakeLists.txt from the main directory of NiftyRec. Select options, set the BUILD_TYPE to Release or to Debug and set all the required paths for additional dependencies if you selected any of the options. Configure and Generate. Browse the 'build' directory and double click on the Visual Studio project file. Click Compile button in Visual Studio. Create self-extracting installer by compiling the corresponding target in Visual Studio.

2.2 Software Overview

2.2.1 Directory Tree



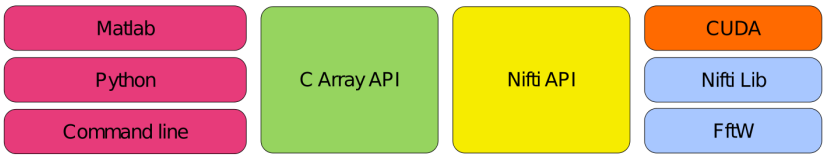


2.2.2 Programming Guidelines

Development of NiftyRec is inspired to the agile programmiong philosophy, Working software is the principal measure of progress, face-to-face conversation between the developers has been the main form of communication. There was a continuous attention to good design and technical excellence, while always opting for simplicity. The programmers tried to make the code as open as they could by adopting meaningful names, following consistent naming conventions and avoiding criptic bits of code. As in Unix Programming, data dominates, the code is based on the data structures defined in the

niftilic `http://niftilib.sourceforge.net/` library and given this choice the algorithms are almost self-evident.

2.3 Programming Interfaces



2.3.1 Nifti Interface

All functions in NiftyRec take as parameters pointers to *nifti_image* data structures, defined in *niftilib*. Developing NiftyRec is simple, one needs to understand what are the fields in the *nifti_image* structure. These structures are well suited to medical images and image in general (in a broad sense, activity, projections, gradients, attenuation image, point spread function, ..) as all the parameters of interest for the image are stored in the structure, allowing one to pass the image and all the information relevant to that image, by one pointer. NiftyRec makes heavy use of *nifti_image* structures, most of the functions take as parameters pointers to *nifti_image* structures which they can then read and modify.

2.3.2 C Array Interface

While NiftyRec internally uses the *niftilib* data structures in order to simplify the handling of images and parameters, it provides a programming interface entirely based on C arrays in order to simplify embedding of NiftyRec into third party applications. The programmer who wants to make use of NiftyRec but does not intend to extend its functinoality, shouldn't be required to learn how to use the niftilib data structures (though they are quite simple). The C Array Interface is based entirely on C arrays and exposes a subset of the functions of NiftyRec that allows one to use all its functionalities.

The source files *et-lib/_et_array_interface.cpp* and *et-lib/_et_array_interface.h* implement the C Array Interface. Each of the functions defined here assembles the required niftilib structures, calls a function from the Nifti Interface,

then destroys the structures that it created.

Note that Matlab and Python bindings are built on top of the C Array Interface, as pictured in figure 2.3.

2.3.3 Matlab

The Matlab Toolbox for NiftyRec is based on mex Matlab extensions. Each of the functions of the NiftyRec C Array Interface has a corresponding mex source file that defines its interface to Matlab. The folder *et-mex* contains the source code of the mex extensions. Subfolders of *et-mex* contain additional Matlab m files and the Matlab inline documentation and manual for NiftyRec. The mex interface is a thin layer on top of the C Array Interface. Each function correponds to one .cpp source file and a .h header in *et-mex*. Edit one of the mex sources in *et-mex* to understand how to create a mex extension for a new function in the C Array Interface.

Note that often mex Matlab extensions are compiled within Matlab by running the *mex ..* command with the source files as parameters. This creates a mex file, which Matlab recognises as an extension. The mex file is actually a shared library (where the extension of the file is renamed); Matlab uses an external compiler to generate the mex and it sets up automatically all the options for the compiler, including where it can find the Matlab libraries (which the mex file builds against). NiftyRec uses the compiler directly to build the mex. A macro in the CMake list file (*et-mex/CMakeLists.txt*) sets the parameters for the compiler and edits the extension of the output dynamic libraries. This allows us to automatically compile the Matlab extensions along with the NiftyRec source.

2.3.4 Python

Python bindings are built on top of the C Array Interface and are based on Python Ctypes. Ctypes is a Python module that allows one to interface dynamic libraries written in C and execute functions that make use of basic C types such as int, float, double, char, arrays and pointers to the former types. There are a few advantages of Ctypes over other methods to interface C code with Python, one being simplicity of use and another being that the interface is independent from the version of Python and from the compiler. Building a Python extension module against the Python libraries defined in Python.h requires the same compiler that was used to compile the Python libraries; this is generally not a problem under Linux, but it can be a problem

under Windows, where Python is typically installed with the self-extracting installer which adds to the system a copy of the libraries that was compiled with a specific compiler, which typically is a commercial compiler. The same problem applies to all the automatic wrappers that create code to be built againsts Python libraries. Ctypes however is a good solution as long as the number of functions to be wrapped is small and as long as is suffices (or is not over complicated) to use only basic C types, which is the case of NiftyRec.

If you edit *et_array_interface.cpp* you will notice that all the functions that are exposed to Python are defined with the *extern "C"* syntax in order to instruct the compiler to treat them as C functions. This solves the problem of using C++ code through Ctypes because of mangling of the function names for overclassing: C++ compilers modify the function names in order to encode the types of the parameters for that particular implementation of the function, though the compiler changes the name in a predictable manner, this is not standard across different compilers.

Editing NiftyRec.py under the NiftyRec folder will clarify how the Ctypes based Python extension module works. NiftyRec.py tells Ctypes to load the dynamic library *lib_et_array_interface* and specifies the types of the parameters for the functions that NiftyRec.py interfaces (which are all the functions that the C array interface exposes). Then NiftyRec.py exposes to the Python programmer a number of functions that take *numpy* arrays as parameters and return objects of the same class; *numpy array* objects expose the Python *array interface*, which allows one to obtain, within the Python environment, a pointer to the data buffer that contains the actual data of the array object; NiftyRec.py extracts the pointer and instructs Ctypes to pass it over to the functions in *lib_et_array_interface*.
All the functions in the C Array Interface are atomic in that they create the data structures that they need and then they free them before they return; when they return data they always write the data into a memory section that was preallocated (they take pointers as parameters) as opposed to allocating the data structure for the result and returning a pointer to that structure (which would require the use of double pointers). This means that it is never necessary to deallocate resources, except for the resources that were allocated before the function call to the C Array Interface. This simple design criterium, which is possible because of the simplicity of the interface, makes the garbage collector of Python responsible for the deallocation of all the resources: numpy arrays for the results are created in NiftyRec.py, the pointer to the C array that is contained within the object is passed to some function in the NiftyRec C Array Interface which writes data into it, then the

array is deallocated by the garbage collector when the object is deleted; the functions in NiftyRec return the object to some calling function and so on, until at some point the object has no references because some function quits and does not return the object (or embeds it as a member of some other object), in which case the garbage collector deallocates all the resources related to that object, including the underlying C array which contained the data.

Chapter 3

User's Guide

3.1 Getting Started

3.1.1 Install Packaged Releases

The packaged releases for some of the most common hardware platforms can be downloaded from the NiftyRec website. These will install on your system the precompiled NiftyRec libraries, binaries, documentation the Matlab and Python Toolboxes and the development headers to use the C API. If a packaged release is not available for your system, then you need to build NiftyRec from source with the CMake build system, following the instructions in the Developer's Guide. This will also optionally install NiftyRec in your system and create a packaged release for distribution of NiftyRec to machines with the same CPU architecture and compatible operating system.

Windows

Double click on the self-extracting installer and follow instructions on screen. By default NiftyRec is installed under *C:/ProgramFiles/NiftyRec/*. This folder contains subfolders with the libraries, binaries, header files for development (see Developer's Guide) and the Matlab and Python extensions.

Linux Debian

Double click on .deb installer and follow instructions on screen. The deb package will install libraries, binaries and headers for development (see Developer's Guide) under */usr/local/lib*, */usr/local/bin* and */usr/local/include*; the Python module is installed amongst the site-packages and will be found automatically by Python; the Matlab Toolbox is installed in */usr/local/niftyrec/-*

matlab and the documentation in */usr/local/niftyrec/doc*.

3.2 Matlab Toolbox

Launch Matlab. Add path to NiftyRec Toolbox.

>> *addpath /usr/local/niftyrec/matlab*

Or add permanently by clicking on File-¿Add path. The path NiftyRec Toolbox is set as an option in CMake. It defaults to '/usr/local/niftyrec/matlab' in Linux and MAC OS and in Windows it's in the NiftyRec install directory, which defaults to C:/ProgramFiles/NiftyRec Open Matlab help and click on Emission Tomography Toolbox to visualize the documentation of NiftyRec Toolbox.

3.2.1 Transmission Tomography

In order to use NiftyRec-TT within Matlab, launch Matlab and add path to the NiftyRec-TT matlab folder:

>> *addpath /usr/local/niftyrec/matlab*

Or add permanently by clicking on File-¿Add path. The path NiftyRec-TT matlab is set as an option in CMake. It defaults to '/usr/local/matlab' in Linux and MAC OS and in Windows it's in the NiftyRec-TT install directory, which defaults to C:/ProgramFiles/NiftyRec. The Matlab interface consists on a mex file that wraps the projection function in the C API. In order to hide the latency due to memory transfers, the function performs multiple projections in one call and the parameters are vectors. See the example below.

Example

```
N_projections = 200;
attenuation = ones(256,256,256);
source = zeros(N_projections,3);
scale  = ones(N_projections,2);
trans  = zeros(N_projections,3);
rot    = zeros(N_projections,3);
source(:,2)=linspace(-1,1,N_projections);
p = tt_project_ray_mex(attenuation,[512,512],source,scale,trans,rot);
for i = 1:N_projections
```

```
    imagesc(p(:,:,i)); colormap gray; pause(0.1)
end
```

3.3 Python Extension Module

The NiftyRec Python module is installed amongst the site-packages by the binary installers and by 'make install'. Open the Python interpreter and import NiftyRec

>>> from NiftyRec import NiftyRec

3.4 C API

In order to build against NiftyRec, include in your project the headers folder, installed under */usr/local/headers* or *C:/ProgramFiles/NiftyRec/headers* (typically) and instruct the linker to link against the NiftyRec libraries installed under */usr/local/headers* or *C:/ProgramFiles/NiftyRec/lib*.

3.4.1 Transmission Tomography

The C API currently implements one function for projection with the raycast algorithm. In order to hide the latency due to memory transfers, the function performs multiple projections in one call and the parameters are arrays:

```
typedef unsigned short VolumeType;

struct float_2
{
  float x, y;
};
typedef struct float_2 float_2;

struct float_3
{
  float x, y, z;
};
typedef struct float_3 float_3;

struct int_3
{
  int x, y, z;
};
typedef struct int_3 int_3;

struct u_int_3
```

```
{
  u_int x, y, z;
};
typedef struct u_int_3 u_int_3;

struct u_int_2
{
  u_int w, h;
};
typedef struct u_int_2 u_int_2;

int tt_project_ray_array(VolumeType h_volume[], u_int_3 volume_voxels,
                         float out_projections[], u_int n_projections,
                         float_2 detector_scale[], float_3 detector_transl[],
                         float_3 detector_rotat[], u_int_2 detector_pixels,
                         float_3 source_pos[]);
```

The function takes as input a 3D unsigned integer attenuation map, stored as a monolithic array of size $(N_x \times N_y \times N_z)$ and fills the float array of size $(ImageW \times ImageH \times N_projections)$ ($N_projections$ needs to be specified as a parameter). The parameter $detector_pixels$ sets the number of pixels of the detector: one ray is cast for each detector pixel ($ImageW = detector_pixels[0], ImageH = detector_pixels[1]$).
All the remaining parameters represent the 3D position of the detector, its size, and the position of the source. Each parameter is an array of length $N_projections$, where each element i of the array represents the parameter for projection i. Parameters are $detector_scale$, $detector_translation$, $detector_rotation$, $detector_pixels$, $source_position$.

$detector_scale$ scales the detector in X and Y (see figure 3.1), if it is set $(1, 1)$, the detector is of size (2,2), (green plane in figure 3.1).

$detector_translation$ is the translation of the detector. If it is set to $(0, 0, 0)$, the detector is centered in $(0, 0, -1)$.
$detector_rotation$ is the rotation of the detector with respect of axis (X, Y, Z).
$source_position$ is the position 3D of the point source.

Figure 3.1: