1 Introduction

Ultrasound (US) has evolved to be one of the major medical imaging systems, being responsible for one of five medical images used for medical diagnosis, and used in nearly all hospitals and clinics [Jensen]. The use of medical US has mayor advantages over other imaging modalities (magnetic resonance and computer tomography) such as: minimal invasion, low cost, ease to use, the ability to obtain images in real time from different perspectives, and no ionizing radiation [Halliwell]. Although these advantages, the use of conventional 2D US may have some drawbacks; the 2D US images represent thin planes of the patients, so choosing the visualization plane of the lesion is difficult since the user must mentally integrate many 2D images to form an impression of the 3D anatomy and pathology; finding the same location of the visualization plane is difficult since the US probe is controlled manually. This problems may be corrected by using 3D US [Fenster].

Three-dimensional ultrasonic imaging is becoming a widespread practice in clinical environments due to the potential applications based on 3-D representation. It provides some interesting benefits: the spatial relationships among 2D planes are preserved, allowing an offline examination of scans previously recorded; renderization and visualization of planes that cannot be acquired because of geometrical constrains imposed by the US probe and the patient anatomy [Estepar]. High quality and instantaneous 3D imaging remains a long term goal of medical US research [Rohlling]. Several 3D US techniques have been reported in the past few years, but these can be coarsely classified as derived from 3D probes and those that obtain a 3D data from 2D B-scans acquired in rapid succession [Estepar]. Using 3D probes, where 3D volume is imaged directly from a single probe position can simplify the reconstruction of the 3D data set since the geometry of the acquired data is known, making real-time 3D reconstruction possible, but this approach does not allow for fine control of the location of the 2D planes, the reconstructed volume geometry and size is constrained by the probe, and the probes are bulkier and more expensive compared with conventional 2D US probes [Honggang]. Because of this, researchers have developed approaches to convert a conventional 2D US transducer into one that is capable of 3D imaging [Fenster 2]. In freehand acquisition, the operator holds the probe and manipulates it in the usual manner over the anatomy to be view and images in arbitrary positions and orientations are acquired. This technique offers special advantages because the operator can select optimal views and accommodate complex patient surfaces and is not limited to the transducer geometry and size [Fenster 3]. However the reconstruction step is still an acute problem with regards to computation time and reconstruction quality because of the sparsity of data [Pierrick].

Mainly there are two different approaches for volume reconstruction. The first kind of methods, reverse approach or Voxel Based Methods (VBM), take the position of the voxels within the volume and find the appropriate pixels within the US images. The second approach, are methods based on solving the forward approach, as tacking the position of each pixel within the B-mode images and finding the appropriate voxel positions within the volume, this methods are called Pixel Based Methods (PBM) [Schiepers]. The last are often more accurate by assigning the pixel values to the nearest voxel and allow several pixels to contribute to the values of each voxel, which is an improvement over the VBM algorithms, and with a fast enough implementation a PBM could be constructed as an iterative method, building the volume along with image acquisition and be made into a near real-time reconstruction. The most common PBM algorithm is the Pixel

Nearest Neighborhood (PNN) and consists of two steps, bin-filling step (BFS) and hole-filling step (HFS); while the BFS depends on the number of images and in its simpler version is fast, the HFS depends on the number of empty voxels left by the BFS and usually is the slower step of the reconstruction [Solberg]. Medical image processing in graphics processing units (GPU) has become quite popular recently because it makes it possible to apply more advanced algorithms and perform computational demanding tasks fast enough for a clinical context [Eklund]. Some reconstruction algorithms have been implemented in GPU to accelerate the reconstruction process: Moon et al. implemented a Bayesian reconstruction method in GPU that is 46.39 times faster than the CPU version of their method and 2.86 times faster than the CPU version of the PNN algorithm [Moon GPU]; Dai et al. optimize the bin filling process in GPU for real time visualization while acquiring the 2D images, using incremental reconstruction [Ohbuchi], after all images are acquired the hole filling step is done also in GPU, however no optimization is made in this step except for parallel computation [Dai].

Samet has provided a useful overview of the octree technique to image processing applications [Samet]. Hierarchical octrees (or quadtrees in two dimensions) offers an efficient method for the spatial discretization of sparse data by recursive decomposition [Saalehi]. K-D trees and octrees are widely adopted to accelerate neighbor search in three-dimensional data for large-scale datasets [Behley]. It is not of our knowledge that octrees have been used in order to optimize the computational time of ultrasound volume reconstruction; in this paper we propose the use of octrees in order to optimize the PNN method in both steps to obtain a fast full reconstruction with high resolution. This paper is organized as follows: Section 2 describes the background of pixel based reconstruction methods, focusing on the PNN method, and the background of octrees and naïve neighborhood search; Section 3 describes the PNN reconstruction method implemented using octrees and Morton keys; Section 4 describes the experiments and present the results of the octree based reconstruction; Section 5 shows the concluding remarks and opens a discussion for future work and possible upgrades.

2 Background

Pixel based volume Reconstruction

Usually the PBM consists of two steps: The distribution or bin-filling step, where the input pixels are traversed and the pixel value is applied to one or several voxels; and the Hole-Filling step (HFS), where the voxels are traversed and empty voxels (voxels that have not been filled in the BFS) are being filled [Solberg].

The most common PBM is the Pixel Nearest Neighbor. In the BFS, the intensity of each pixel in the 2D ultrasound images is assigned to the nearest voxel in the 3D ultrasound volume; the contribution of multiple pixels to a single voxel usually are averaged [Doud], but other variants are possible, like keeping the max value, the most recent value or the first value [Solberg] (FIGURA); in order to find the nearest voxel to the pixel the 2D US image coordinates must be converted to global coordinates [Moon], in the freehand approach a transformation matrix from the B-scan coordinate system to the reconstruction volume coordinate system has to be predetermined by a spatial calibration [Dai]. If the images are acquire with sufficient separation (less than one voxel for the PNN) a second step will not be needed [Gobbi]. In the HFS the algorithm loops over the target volume and fill the gaps; for every empty voxel, non-empty neighboring voxels in a certain radius around the empty one are averaged into the resulting value, usually a growing radius starting at 1 voxel is used, if non-empty voxels are found the region will grow until non empty pixels are found or a maximum radius is reached [Miller], this may be computationally expensive, so a fixed radius may be used, the fixed radius may be the maximum radius used in the last approach or one that is function of the point spread function of the ultrasound [Estepar 2]. (FIGURA). In order to avoid the visible boundaries between the voxels assigned directly by the 2D ultrasound images during the BFS and the interpolated voxels computed during the HFS [Doud], a weighted distance can be used in the HFS in order to avoid far away pixels to contribute on the voxel and have smoother transitions, where the weight is the inverse distance between the center voxel and the non-empty voxel [Chen].

Octrees and Morton Key

The octree is a hierarchical representation of a $2^n x 2^{nx} 2^n$ array of unit cubes or voxels and it can be used as the primary data structure of 3D applications in image processing, such as object representation. An octree is a tree where the root node depicts the universe which encloses the entire object in a cubic space, then the space is recursively divided into octants whose nodes are either leaves or have eight children (FIGURA) [Rambally].

Usually the octree is stored as a record containing ten fields: eight fields contain pointers to the children; one contains a pointer to the parent; and the last describes the content of the field (color of the voxel) [Rambally]. Another popular way to encode the octrees is a linear octree encoding depending on Morton set, where no pointers are allocated to keep a spatial order of its nodes; instead, each leave is assigned a unique locational code formed by a sequence of octal digits that traces a path from the root to the node, where the digits identify the set of branches that must be traversed [Song]. This function maps each object to a unique key (Morton Key), where each key corresponds to some composite data describing the physical data inside the reconstruction space [Warren].

For naïve radius neighbor search in an octree, the tree has to be traversed from its root recursively and investigate octants overlapping the search circle defined by an arbitrary query point $q \in \mathbb{R}^3$ and a radius $r \in \mathbb{R}$. When an overlapping leaf octant is reached, all points p inside the octant are checked if $\| p - q \| < r$. With this approach only points inside the overlapping leaf octants are compared and large subsets of points that are irrelevant for the query are discard [Behly].