A Virtual Ultrasound Imaging System for the Simulation of Ultrasound-Guided Needle Insertion Procedures

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Abstract. In this paper we describe a virtual ultrasound imaging system for the simulation of ultrasound guided needle insertion procedures, which is designed to improve the early training stages of interventional radiology trainees. A pair of calibrated magnetic 3D motion sensors are used to capture the position and orientation of a mock ultrasound probe and needle, whilst emulational ultrasound images are generated in real-time from a labelled volumetric data set that is non-rigidly aligned to a physical model of human body. To achieve a realistic simulation of ultrasound imaging, a set of volumetric textures are constructed to represent the typical appearance of ultrasound images, and an alpha blending method is applied to produce the radial blurring effect. The procedures of volumetric registration, sensor calibration, construction of texture bank, and image rendering, are presented.

1 Introduction

The insertion of a needle (or equivalent device) into a patient is frequently performed in a variety of clinical routines, such as drainage of abscess, relief of blockages in the kidneys or the liver, radioactive seed implantation, and biopsy of deep tissues. To ensure an accurate placement of the needle, such procedure is usually guided by real-time feedback from a 2D ultrasound display. However, acquisition of the spatial reasoning and hand-eye co-ordination skills for such ultrasound-guided needle insertion procedure requires a specialised training process. Conventionally, this training is performed on the basis of the so-called *see one, do one, teach one* paradigm [1], in which the trainees, after observing a large number of such procedures, practice on live patients under supervision of skilled radiologists. The evaluation of the acquired skills in such training process is often subjective, and it is often risky for the patients when such invasive procedure is performed by less skilled radiologists.

An obvious solution is using simulation systems for the training of such interventional procedures. Some systems based on physical phantoms have been developed (e.g., the breast ultrasound phantom from SIEL Ltd.). However, such physical systems are often designed for specific abnormalities, and high in cost because of the use of a real ultrasound machine. A more feasible alternative is computerised simulation, based on virtual reality (VR), in which the complete environment is simulated within a computer, or augmented reality (AR), in which physical and virtual worlds are interconnected. Integrating computer visualisation techniques and physical components such as haptic feedback devices and/or mannequins, AR simulators can be used to achieve a more realistic experience for the training of interventional operations with visual feedbacks. Holbrey $et\ al$ [2] present a simulation system for vascular suturing training, based on a haptic feedback device, stereo display, and Finite Element Models. Gorman $et\ al$ [3] developed a system incorporating a mannequin and a haptic feedback device for the simulation of lumbar puncture procedure, which is based on offline CT data, and so has no real-time visual feedback. Simulators for fluoroscopy (real-time or near real-time X-ray based 2D imaging) guided procedures [1, 4] are closer in nature to the ultrasound guided simulation system presented in this paper. The advantage of fluoroscopy over ultrasound is that the direction of imaging is far less important than with ultrasound due to the absorbency/reflection properties of ultrasound. However, ultrasound is fully real-time, flexible, and inherently safe, while exposure to X-ray should be minimised. Alterovitz $et\ al$ present a simulator for ultrasound guided needle insertion [5]. However, this is a 2D computer only simulator, which does not simulate probe motion or any 3D aspects of the procedure.

We have previously described a prototype simulation system for ultrasound guided needle insertion procedures [6]. In this initial system the physical model of the human body is a plastic mannequin, on which the user can perform operations such as ultrasound scanning and needle insertion. The position and orientation of the mock ultrasound probe and the needle are captured by a pair of magnetic 3D motion sensors. Virtual ultrasound images are generated from a volumetric CT data set that is non-rigidly registered to the mannequin surface, and rendered in real-time to guide the needle insertion procedure. The initial evaluation of the system, performed using a set of unskilled individuals and a set of experienced clinicians, reveals that, after structured practice on the simulator,

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the positioning and hand-eye co-ordination abilities can be clearly improved. However, this initial system has a number of shortcomings. Firstly, since the synthetic images are generated directly from a volume of CT data, they look more like CT images, rather than the desired ultrasound feedback. Additionally, the plastic mannequin surface is too hard for a needle to penetrate. Hence instead of a real needle that can be used to insert into the body, the sensor is attached to a wooden stick via a sliding mechanism to mimic the insertion process. The system has been further developed to achieve more realistic simulation of the procedure. In addition to the construction and use of a penetrable model of human body, a Laplacian pyramid based approach is developed to generate synthetic textures from ultrasound image samples, and a 2D alpha blending technique is adopted to produce the ultrasound-specific radial blurring effects. With the emphasis on these newer improvements, this paper also briefly describes other aspects of the system (e.g. volume registration and sensor calibration) to provide a complete overview of the system.

2 System Implementation

The hardware of our simulation system consists of three components, a standard PC (Dual Intel® Xeon™ CPU 3.20 GHz, 2.0 GB of RAM, running Microsoft® Windows® XP™ Professional), a full scale penetrable model made of latex plastic and foam, and a pair of Ascension PCIBirds magnetic 3D position/orientation sensors. One of the sensors is rigidly attached to a spare ultrasound probe, and the other attached to a standard biopsy needle. Figure 1 illustrates the hardware setup of our simulator.

To produce synthetic ultrasound images, there are a number of tasks to be accomplished (Figure 2). Firstly, a virtual human body, in the form of a volumetric CT data set, is obtained from a human subject. The volume is manually segmented so that each voxel in the volume is assigned a label that indicates the property of the voxel, and then registered to the surface of the physical model (Section 2.1). Secondly, the motion sensors are calibrated so that the position and orientation of the probe/needle they attached to can be correctly captured and represented (Section 2.2). Thirdly, a bank of volumetric textures are constructed from real ultrasound images to represent the typical appearance of the objects in the segmented volumetric data (Section 2.3.1). During interaction, given the position/orientation of the probe, a scan plane is determined. The image is produced by raster scanning through the pixels in the ultrasound portion of the plane, and projecting each point to the corresponding point in 3D space so that its greylevel can be determined. In addition, a 2D ray-casting method is applied to produce the shadow effects caused by bones and air bags in the virtual body. The constructed image is then rendered using an alpha blending routine to simulate the radial blur effect (Section 2.3.2).

Figure 1. Overview of hardware setup.

2.1 Registration of Volumetric Data to The Model Surface

The simulator renders "virtual ultrasound images" based on a CT volumetric data set acquired from a real human. The data is first manually segmented by our cooperating expert radiologist, then registered to the surface of the physical model in a three-stage process. Firstly, the body surface embedded in the volumetric data is extract by manually annotation of the slices, and the model surface is extracted by passing a calibrated motion sensor over the surface of the mannequin model. The second stage involves a rigid alignment of the surfaces by the Iterative Closest Point (ICP) algorithm [7]. Subsequently, for the surfaces to be completely aligned, a non-rigid registration process, based on the RanSaC algorithm [8] is performed. This yields a quadratic function, which can be used to warp the volumetric data offline to a new volume that is aligned to the model surface. Once the warped volume has been formed, online calibration is simply a process of rigid scale and offset between the volume co-ordinate system and the world co-ordinate system.

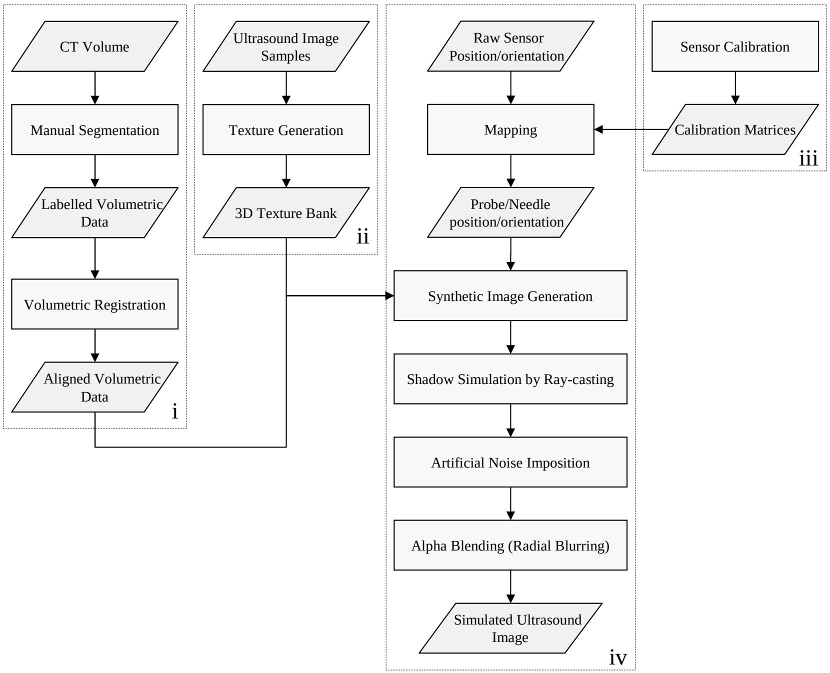


Figure 2. Simulation process of ultrasound imaging.

2.2 Sensor Calibration

Although it is not always possible to place the motion sensor at the position that we want to measure (e.g. the tip of the needle), or orient it in the direction we want to measure, it is possible to rigidly attach the sensors to the probe and needle, and estimate a calibration function to map the sensor output to the desired values. In case of the ultrasound probe, the calibration point is located at the centre of the end of the probe, and the mapping function from the attached sensor to the calibration point is estimated from multiple unique position samples using a standard Least Square Fitting method. Similar approach can be applied to the calibration of the probe direction, as well as the calibration of the needle. A complete description of the sensor calibration process can be found in [6].

2.3 Generation of Synthetic Ultrasound Images

Ultrasound guided needle insertion requires real-time visual feedback from the simulator. It is difficult to model the physical properties of an real ultrasound system. However, it is possible to simulate these properties by a series of common 2D effects. These include texture mapping, artificial noise imposition, and radial blurring.

2.3.1 Construction of Texture Database

A set of volumetric "solid textures" [9, 10] (one for each visually distinct tissue type) is learned from sets of hand selected 2D ultrasound examples. Solid textures are volumes for which the surfaces appear similarly textured if cut by any plane (or other surface). There is a large body of literature on the generation of synthetic 2D textures, but much less on solid texture generation. This is probably due to the fact that they are not currently as widely used for a number of reasons including; Consumer graphics hardware architectures, higher memory requirements than 2D textures, and the comparative difficulty in making volume textures anisotropic. However, they are ideally suited to our application as 2D textures cannot model the effect of sensor motion in three dimensions. 2D synthetic texture methods fall broadly into two categories; i) Cut-and-paste based methods (e.g. [11]), in which patches of training images are pasted together to form an new texture, and ii) Image statistics based methods (e.g. [12]). We have found approach i) does not easily extend to learning 3D solid textures from 2D examples. Our approach is to use a Laplacian image pyramid [12] (with 3 or 4 levels) to represent the image and volume statistics, and to match the statistics of the volume to the training images. A Laplacian image pyramid is a set of images (or volumes) generated from a single image by iteratively applying a low pass filter and subtracting the result from the previous image generated. This is a form of frequency decomposition. We use a 256 bin greylevel histogram at each level of the Laplacian pyramid to capture the training data statistics ($P_l(g)$). We also form two dimensional histograms to capture the joint greylevel probability distribution of each level and the level below ($P_{l,l-1}(g_l, g_{l-1})$). To generate the solid texture we start at the lowest (most coarse) level of the Laplacian pyramid and sample greylevel values from $P_l(g)$. Subsequent levels of the pyramid are generated based on a weighted combination of $P_l(g)$ and $P_{l,l-1}(g_l, g_{l-1})$:

$$P_l(g) = K_l P_l(g) + (1 - K_l) P_{l,l-1}(g_l, g_{l-1}) \quad (1)$$

Where K_l is typically 0.6 for all levels except the top (highest frequency) level, where it is 0. The use of $P_l(g)$ compensates for the data sparsity at the lower levels which can lead to textures that are too regular. This is unnecessary at the top (highest frequency) level as sufficient data is available. A tessellating solid texture (typically 32x32x32) is generated from the Laplacian volume pyramid generated by the sampling process by use of a low-pass filter that assumes 3D wrapping at the edges of the volume. This is a very fast process as it does not rely on searching through the training set (e.g. [13]) or iterative optimisation (e.g. [12]). Examples of training textures and slices through generated solid textures are given in figure 3.

a)

b)

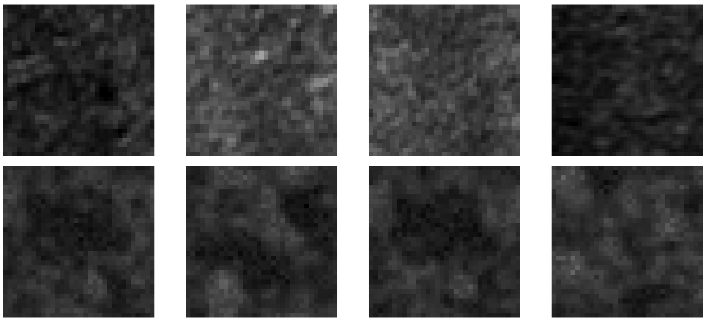
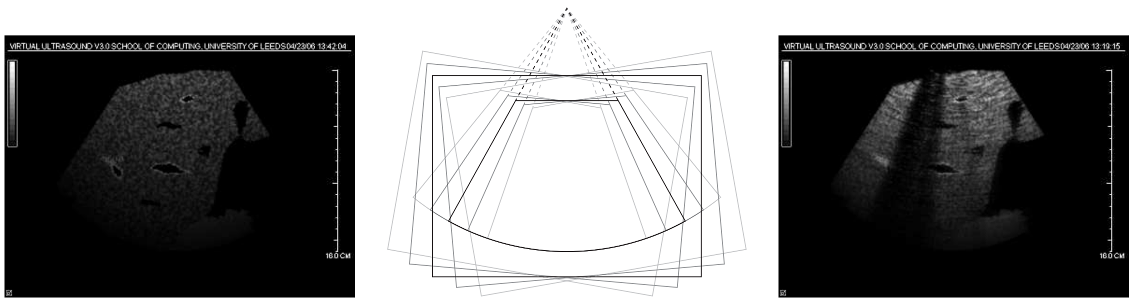


Figure 3. a) Training textures (Liver), b) Slices through generated texture

2.3.2 Simulation of Ultrasound-Specific Artifacts

With the generated textures, an initial ultrasound image can be generated by raster scanning through the pixels in the ultrasound portion of the scan plane, and projecting each pixel to the corresponding voxel in the 3D volume space so that its label can be determined. The pixel's label and its 3D coordinates are then used to sample the corresponding texture to determine the greylevel of the pixel. An example of the intermediate result at this stage is shown in Figure 4 (a). However this image is not much close to real ultrasound output due to the lack of some ultrasound-specific artifacts, such as speckle noise, shadows, and radial motion blurring. The speckle effect can be simply simulated by adding Gaussian distributed artificial noise to the image pixels (We currently use $\sigma = 15$ for the Gaussian noise). Since ultrasound pulses do not penetrate bones or air, a shadow will be cast behind these objects if they present in the scan plane. We simulate the shadowing effect by a 2D ray-casting approach. Regarding the centre of the end of the ultrasound probe as a spot light, we compute the greylevel decrement of each image pixel according to the number of bone pixels (or air pixels) along the straight line segment that connects the spot light and the pixel; the more bone pixels appear along the line segment, the darker the pixel is. In fact, note that the ultrasound image is generated by a top-bottom raster scanning process, both the speckle and shadowing effects can be produced in one scan of the full image, and hence maintain a satisfactory frame rate in real-time interactive mode.

The radial blur effect creates blurs around a specific point in an image, simulating the effects of a swirling camera. This effect can be used to simulate the radial scanning motion of a real ultrasound transducer. However, the traditional method that computes the blurred image by a convolution operation is too computationally expensive to be applied in real-time. Therefore, we have made use of the power of modern graphics cards to achieve the same effect. The traditional blurring convolution can be viewed as a weighted sum process that adds up the original image and a number of its weighted copies with certain offsets (or rotations). This can be performed by the alpha blending function that is efficiently implemented by most modern graphics cards.We draw the generated image many times to create the radial blur effect, varying the angle of rotation about the blurring centre, and increasing the alpha level while the angle increases. Figure 4 (b) is an illustration of the alpha blending process, and an example of the final ultrasound image generated by our simulator is given in Figure 4 (c). It is worth to emphasise that, though consisting of a series of tasks, the image generation and rendering process is still much efficient in computation. The average frame rate of our ultrasound simulator is 12-13 fps, which is very close to the 16 fps rate that is commonly used in clinical radiology.



(a) (b) (c)

Figure 4. (a) A "raw" synthetic ultrasound image without additional artifacts; (b) Illustration of the alpha blending process for radial blur effect; (c) An example of the final simulated ultrasound image.

3 Discussion

We have presented the latest developments of our simulation system for ultrasound guided needle insertion procedures. These developments have largely improved the fidelity of the simulator, in terms of the synthesis of much more realistic ultrasound images, and a better model of the human body on which needle insertion can be performed. Our collaborative radiologists were much impressed by the simulated procedure and its reality was highly approved, though an objective assessment of the system is still indispensable. Future work will be focused on three aspects. Firstly, at present only a model of the front body is in use, which means that simulation of needle insertion at the back of the body (e.g. needle insertion into the kidneys) is not currently available. A model of the back human body is being created, and shortly it will be added to the system. Secondly, the current simulator is based on a static volumetric data set. Therefore motions of internal organs caused by patient breathing and heart beating, which can be observed in real ultrasound imaging, are not modelled. A long-term plan is to construct a self-deforming model of the human body, and thus simulate the motions of the internal anatomies. Thirdly, based on the initial evaluation of the system as presented in [6], a comprehensive evaluation scheme, covering clinical radiology, psychology and computer sciences is being designed and will be performed in due course.

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