DEVELOPMENT OF A FAST AND ROBUST 2D-3D REGISTRATION METHOD FOR IMAGE-GUIDED RADIATION THERAPY

Jian Wu and Jatinder Palta
Dept. of Radiation Oncology, University of Florida

Minho Kim and Jorg Peters
Dept. of Computer and Information Science and Engineering, University of Florida

Sanjiv S. Samant
Dept. of Nuclear and Radiological Sciences, University of Florida

BACKGROUND

New GPU hardware-based approach for fast computations in medical physics

- GPUs are fast…
  - 3.0 GHz dual-core Pentium4: 24.6G FLOPS
  - NVIDIA GeForce 8800 GTX: 520G FLOPS
  - NVIDIA GeForce 8800 GTX: 128 stream processors
- GPUs are getting faster, faster…
  - CPUs: 1.4 x annual growth
  - GPUs: 1.7 x (pixels) to 2.3 x (vertices) annual growth
  - Driven by multi-billion dollar video game market

Flexible and precise

- Modern GPUs are highly programmable
  - Programmable pixel, vertex, and geometry engines
  - Solid high-level language support
- Modern GPUs support "floating point" precision
  - 32-bit floating point throughout the pipeline

Application in 2D-3D registration

- 2D-3D registration—patient positioning and setup verification.
- Does not require on-board CBCT
  - CBCT—$300k-$500k
  - NVIDIA GeForce GPU—$500 (imager not counted)
- Much lower imaging dose—achieving comparable accuracy for rigid and semi-rigid anatomy.
  - CBCT imaging—20 mSv
  - 2D kv x-ray imaging—1 mSv
- Can be computed as fast as 3D-3D registrations. If image acquisition time is counted, 2D-3D is faster.

Fast DRR Calculation Algorithms:

- Fast ray-tracing algorithms (Siddon, 1985; Jacobs, 1998)—slow but most accurate;
- Using pre-calculated DRR library (Clippe, 2003; Jans 2006)—interpolation error; limited range;
- Using attenuation field (Russakoff, 2005; Rohlfing 2005)—complicated, less accurate;
- Utilizing GPU hardware (Khamene 2005; Ino, 2006)—fast and accurate;
- Other methods (Wobbled splatting, shear-warp factorization, etc.)—less accurate.

METHODS

GPU-Based Fast DRR Calculation

- Fragment processor used.
- Texture-based volume rendering for DRR generation—Both 3D texture mapping and alpha blending procedures are hardware-accelerated—significant performance improvement.
- Stream programming model
  - Organizing data into streams—stored as texture data on the video memory.
  - Expressing computation as kernels that operate on streams—implemented as a fragment processor (FP) program.

GPU—NVIDIA GeForce 8800 GTX

Stream Processors	128
Core Clock (MHz)	575
Shader Clock (MHz)	1350
Memory Clock (MHz)	900
Memory Amount	768 MB
Memory Interface	384-bit
Memory Bandwidth (GB/sec)	86.4
Texture Fill Rate (billion/sec)	36.8

- 32-bit per component floating point texture filtering and blending.
- NVIDIA GeForce 8800 GTX: 520G FLOPS
  (3.0 GHz dual-core Pentium4: 24.6G FLOPS)
- Full OpenGL® support, including OpenGL 2.0

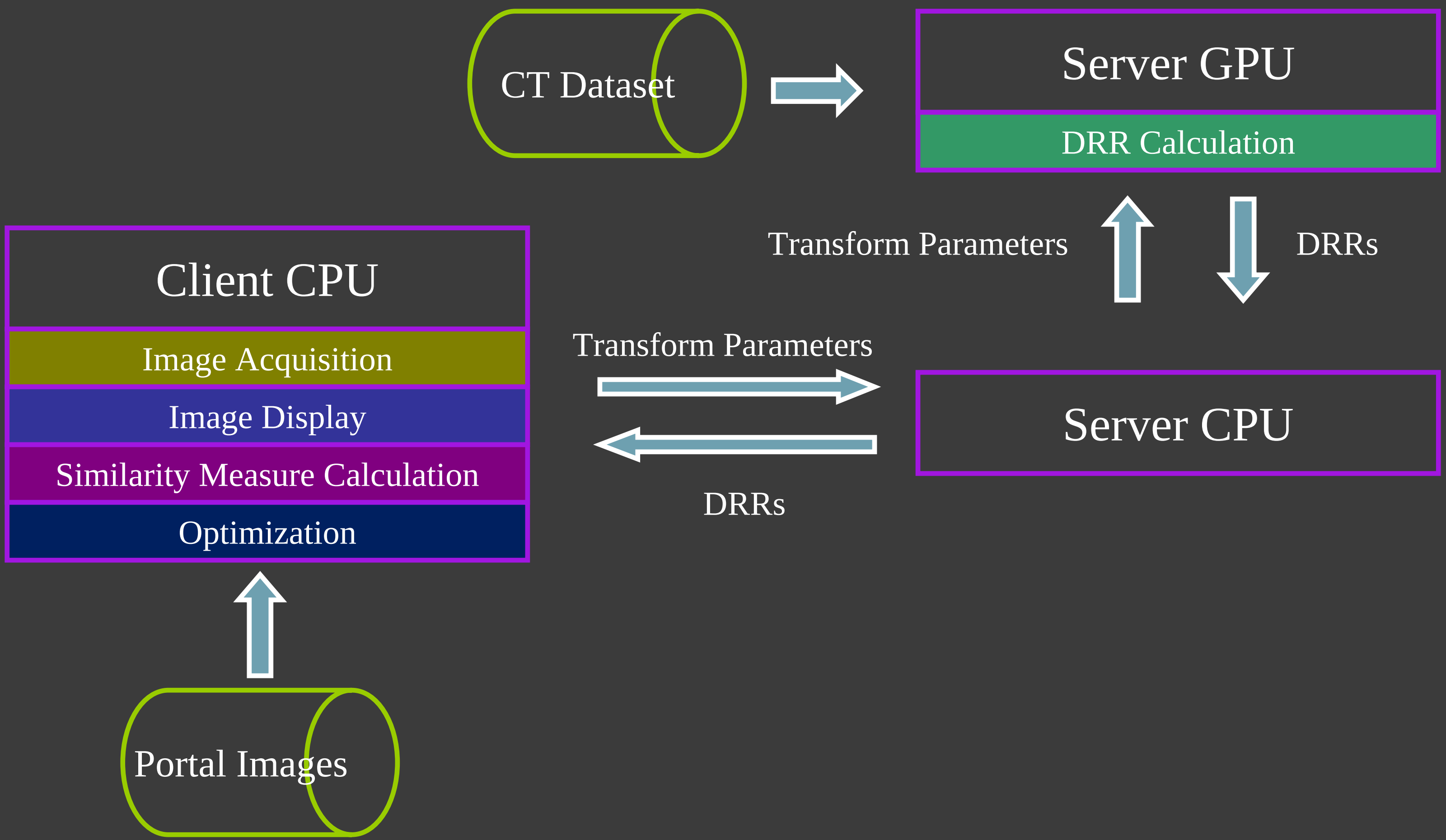


Figure. Flow-chart for Current GPU-Based 2D-3D Registration System

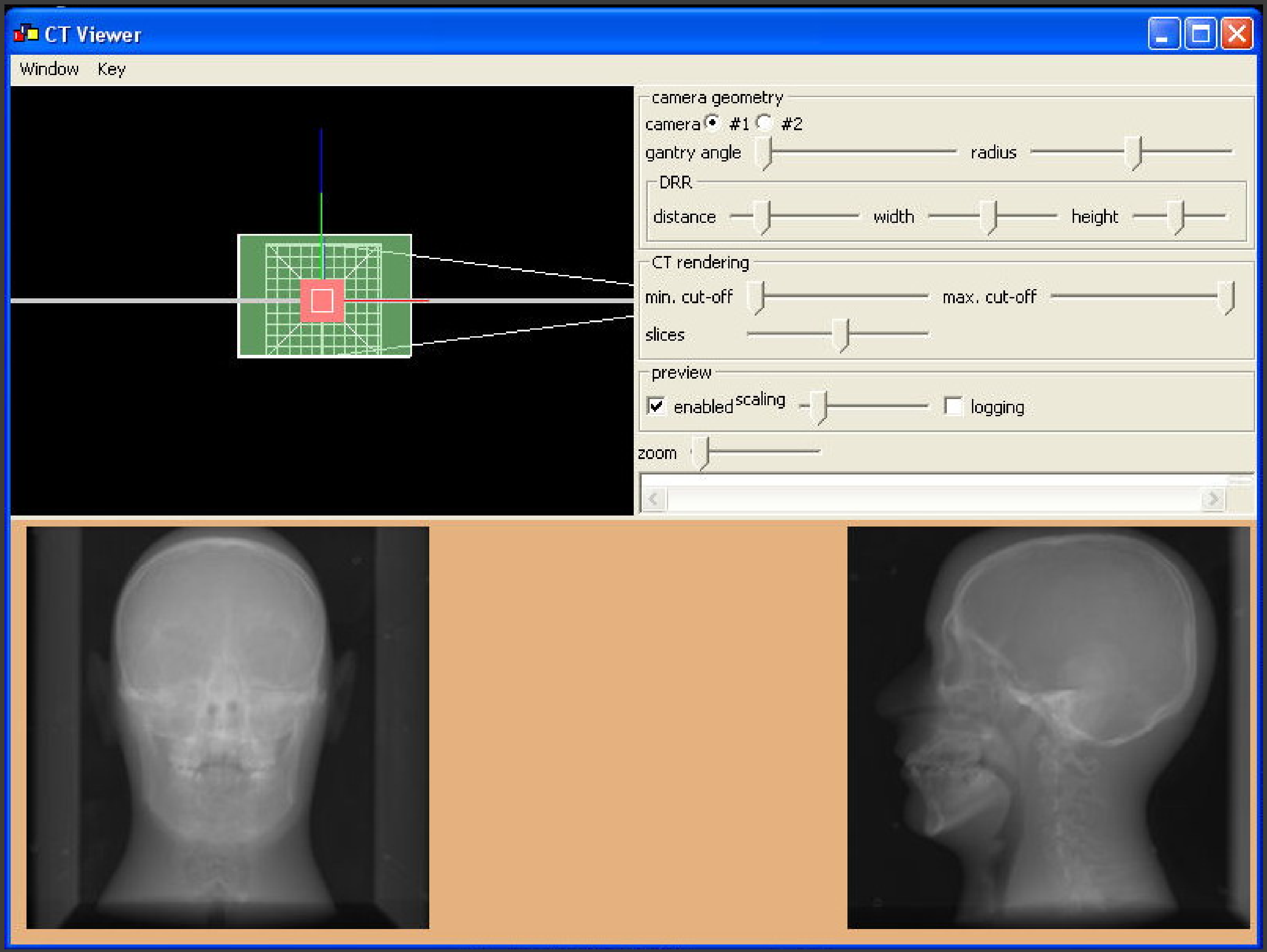


Figure . GPU-based 2D-3D registration software—DRR server interface.

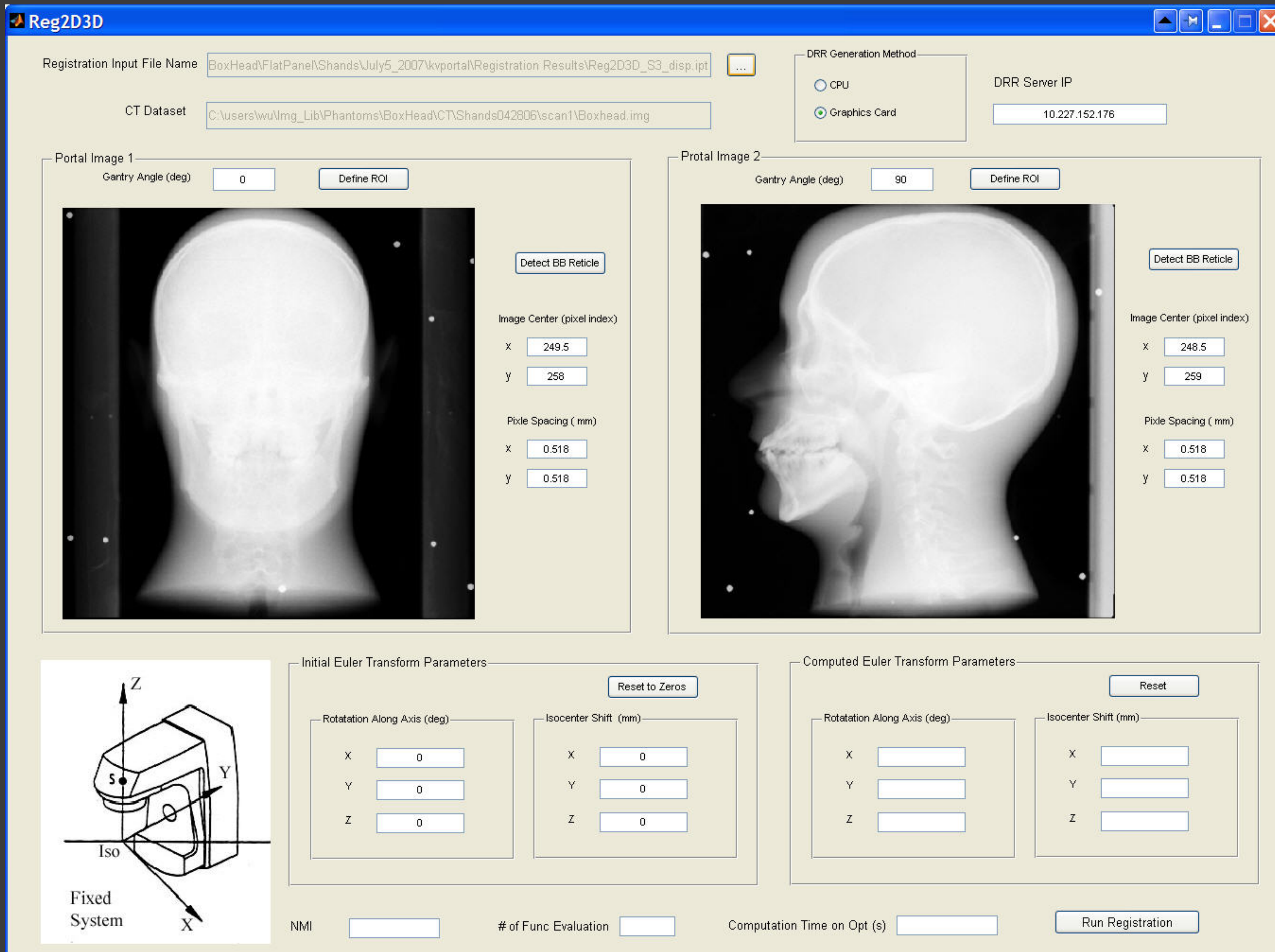


Figure 6. GPU-based 2D-3D registration software—client interface.

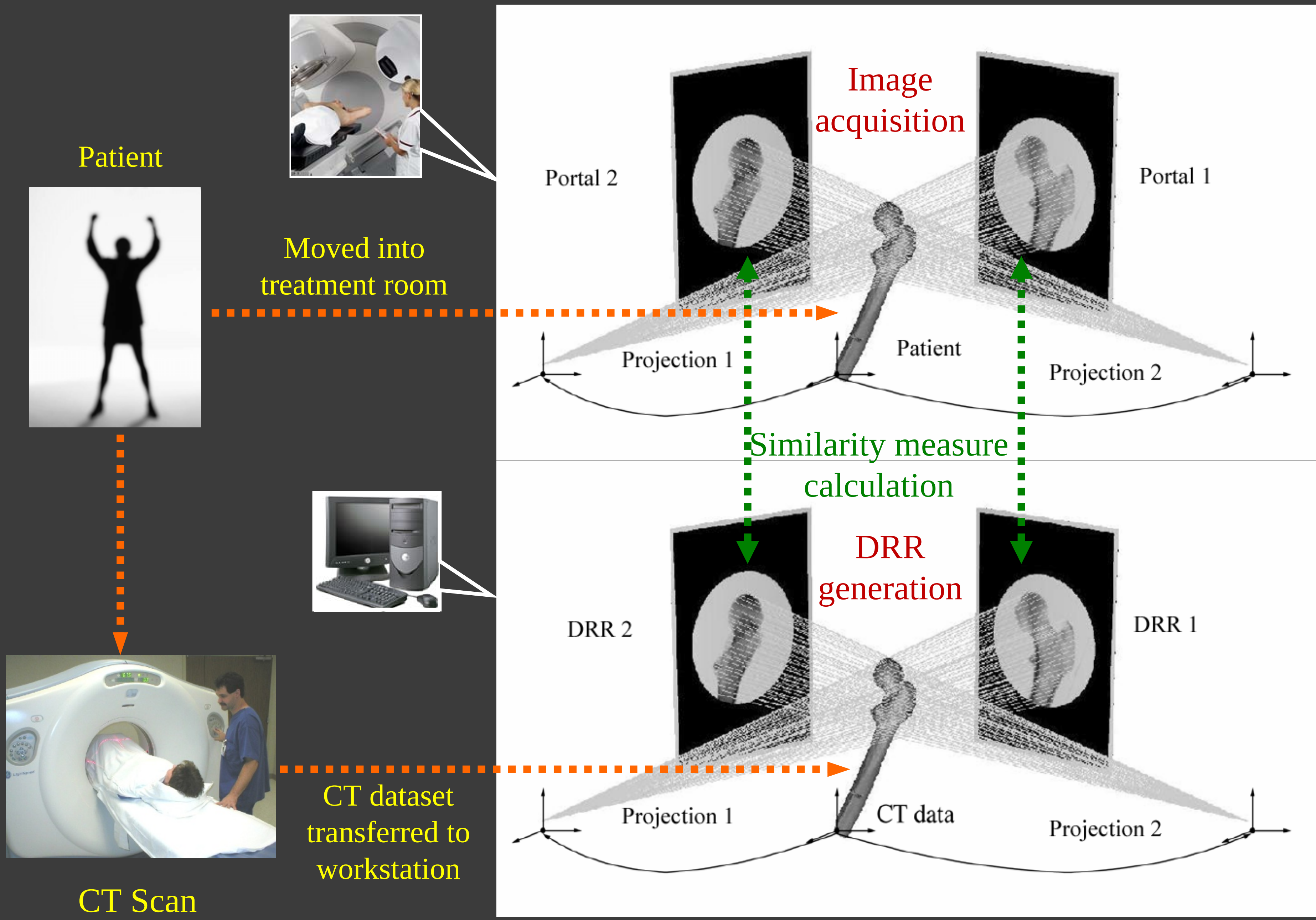


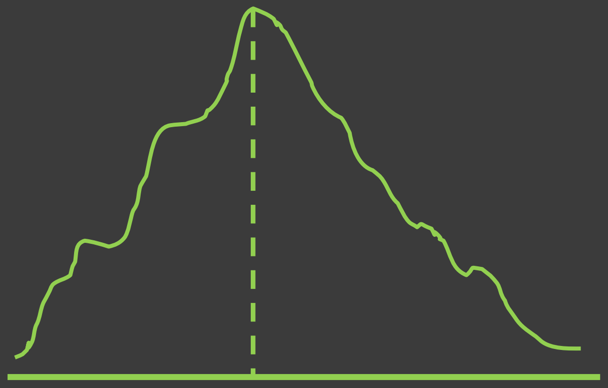
Figure. Intensity-based 2D-3D registration method

Problem with intensity-based algorithms

—Local optimum trapping (32% failed, Russakoff 2005)

How to identity ‘bad’ registrations and avoid being trapped into local optima?

- Knowing the proximate value of the global optimum and the function shape would help to identify local optima.
  - The value of the global optimum is about the same when we register the same patient.
  - It varies from patient to patient.
- For patient, automatically learn the global optimum value and the shape of the objective function—RQE construction.

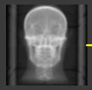


A typical objective function for registration

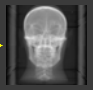
RQE Construction

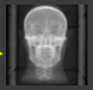
Ref

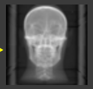
Random Deviation

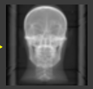


Registered Target Image









X-shift (mm)	Y-shift (mm)	Rot (deg)
0.25	-0.32	0.02
-0.85	0.58	0.47
1.56	-2.15	-0.78
-2.55	0.18	-2.76

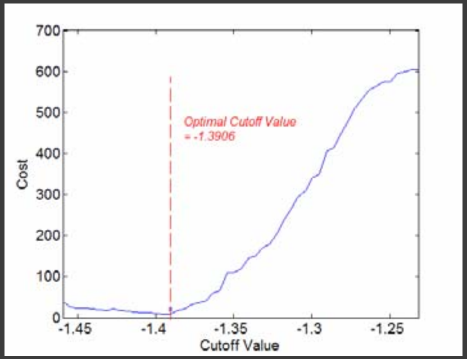
Bad Reg?
N
N
Y
Y

Measure
1.5317
1.5191
1.4850
1.3975

Optimal Threshold

$$\text{Cost} = C_{FP} \cdot FP \cdot (1 - D) + C_{FN} \cdot FN \cdot D$$

Note: FP, the count of false-positive; FN, the count of false-negative; C_{FP}=1, the cost of false-positive; C_{FN}=10, the cost of false-negative; D, the probability of bad registrations in the training dataset.



Registration Error Quantification

Quantified as—the average voxel shift over the image volume.

- Normalized units of rotations and translations were calculated that equal changes of each transform parameters in the normalized parametrical space produce approximately equal voxel shifts when averaged over the image volume.
- The normalized units for rotations along X, Y, or Z axes were computed separately.
- The rotation center was user-defined.
- The average voxel shift was only calculated within the region-of-interest.

Consequently, a Euclidean metric can be used on the parameter space to determine distances between transformations.

MATERIALS

- Anthropomorphic cranial phantom.
- Phillips Brilliance Big Bore CT scanner
  - CT dataset size: 512x512x283
- KV imaging
  - Elekta Synergy S Linac, single image mode.
  - Image size: 512x512
- MV imaging
  - Elekta iView flat-panel EPID
  - Image size: 1024x1024 down-sampled to 512x512
- Dell XPS 710 desktop PC
  - Intel® Core™2 Duo Processor E6300 (2MB L2 Cache,1.86GHz,1066 FSB)
  - nVIDIA GeForce 8800.

RESULTS

2D-3D Registration Performance

- Server and client in the same machine
  - Current: 5-15 sec
  - Goal: <5 sec
- Server and client connected by network
  - Current: >30 sec
  - Goal: <5 sec

TABLE I. RQE performance. Test dataset 1 involves small phantom setup displacements ($\Delta \leq 5$mm and $\Delta \leq 3°$). Test dataset 2 involves medium displacements ($5\text{mm} < \Delta \leq 10$mm and/or $3° < \Delta \leq 5°$). Test dataset 3 involves large displacements ($10\text{mm} < \Delta \leq 15$mm and/or $5° < \Delta \leq 7°$).

	Sensitivity (95% CI)	Specificity (95% CI)	NPV	PPV
Training dataset	0.992 (0.955-1.000)	0.923 (0.840-0.971)	0.986	0.953
Test dataset 1	1.000	0.910	1.000	0.457
Test dataset 2	1.000	0.949	1.000	0.893
Test dataset 3	0.930	0.810	0.979	0.545
All test dataset	0.957	0.858	0.988	0.608

CONCLUSIONS

- GPU-based fast DRR calculation can provide near real-time 2D-3D registration for patient positioning and position monitoring.
- As part of an automated patient positioning system, RQE can be combined with a 2D-3D registration algorithm to improve algorithm robustness by avoiding local optima or immature terminations.
- The implementation of RQE in the clinic could potentially reduce the involvement of the radiation oncologist or therapist for routine pre-treatment patient positioning verification, while increasing accuracy.

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THANK YOU!