Towards Dynamic Patient-CT Registration for Soft Tissue Interventions

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Clinical Application

Soft tissue interventions, such as to treat cancer in the kidney and liver.

NCI estimates for 2011 cancer-rates in U.S. (new cases/deaths):

Kidney: (26,190/19,590); Liver: (60,920/13,120)

• Interventional Radiology

  – Minimally invasive procedures performed under real-time image guidance
  – Example: percutaneous needle biopsy or ablation of tumors

• Surgery

  – Tumor resection or ablation
Clinical Problem

• Pre-operative CT imaging provides:
  – Diagnosis of disease
  – Plan for intervention

• Intra-operative challenge:
  – Judging correspondence between patient anatomy and pre-op CT (i.e. “what is my interventional plan?”) is hard
  – Ultrasound guidance is also difficult to interpret relative to cross-sectional CT images

Figures: http://athletics.wikia.com/wiki/Planes_of_Motion
Standard Approach to Clinical Problem

• Typical Navigation System
  – Track patient
  – Track surgical tools relative to patient
  – Register patient to pre-op CT using fixed fiducial markers
  – Assume registration does not change during intervention

• Problems for this Approach:
  – Patient/CT registration is difficult to establish in absence of fiducials
  – Registration changes when patient moves or tissue deforms
    => need real-time update
  – Real-time update should not impose workload on medical professionals
    => need automatic real-time update
    (i.e. should not primarily rely on manual sampling of fiducials)
Clinical Situation

- Tracked imaging data (ultrasound) is acquired during the intervention.
- Tracking system has error/uncertainty (*F_i = F_i ΔF_i).
- We wish to estimate the transformation from tracker space to CT space (*F_{CT}).

*F_{CT} is in general a **non-linear** mapping (non-rigid transformation).
*F_{CT} is **not constant** due to patient motion and deformations.

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\[ *F_{CT} \]

---

\[ *F_1 \]
\[ *F_2 \]
\[ ... \]
\[ *F_N \]
Research Goals

• Clinical Goal
  – Aid navigation of soft tissue interventions through dynamic registration of real-time imaging data.

• Technical Goal (Approach)
  – Develop an algorithm to update and improve a patient-CT registration as intraoperative imaging data (such as B-mode ultrasound) accrues and changes over time.
  – Provide automated suggestion for the “next-best image” that would constrain/improve a CT registration based on tracked B-mode ultrasound imaging.
  – Supplement ultrasound registration with surface images, feature locations, etc. and integrate all data sources in a hybrid registration approach.
Bayesian Methods

Updating a Registration with Real-Time Data

Bayesian Method: Given a prior belief on the value of some parameter, we can update our belief in light of new evidence.

θ: parameter we wish to estimate from data
X: observed data

P(θ): prior probability
P(X|θ): likelihood of θ
P(θ|X): posterior probability (what we want to know)

Initialize) Choose P_0(θ) (uniform distribution if completely unknown)
Step 1) Obtain new data X_i
Step 2) Update probability in light of new data: \( P(\theta | X_i) \propto P(X_i | \theta) P_i(\theta) \)
Step 3) Now set \( P_{i+1}(\theta) = P(\theta | X_i) \) and iterate from step 1

Bayes Rule:

\[
P(\theta | X) = P(X | \theta) \frac{P(\theta)}{P(X)}
\]

\[
P(\theta | X) \propto P(X | \theta) P(\theta)
\]

Note: θ must be such that it defines a likelihood measure on a given set of data.
Bayesian Methods

Example: Normally distributed data

\( \mu = (\mu, \sigma^2) \) (mean & variance of the Gaussian)
\( X = \) samples assumed to derive from a Gaussian distribution

\( P(\mu): \) prior probability
\( P(\mu|X): \) posterior probability
\( P(X|\mu): \) likelihood

Figure: *Introduction to Machine Learning, 2nd Ed.* by Ethem Alpaydin
Bayesian Methods

Applied to the surgical navigation context:

\[ \theta = F_{CT} \] (coordinate transformation from tracker space to CT space)
\[ X = \text{tracked ultrasound imaging stream (also features, surface data, etc.)} \]

Challenges for this model (open questions):

How to define a probability density on the data given a certain registration value?

i.e., how to calculate: \( P(X|\theta) \)

How to efficiently solve for the most probable registration value over the entire search space?

i.e., how to efficiently maximize \( P(\theta|X) \) given a means to calculate \( P(X|\theta) \)?
Limitations of Ultrasound Registration

Similarity Metric over Translations:

Similarity Metric over Rotations:
Hybrid Registration
Constraining a Registration with Enough Data

Pre-Op CT
CT Surface Model

Tracked Range Data

CT Derived Models
CT Vessel Model

Camera View

Navigation System Display

Hybrid Registration
$F_{CT\leftarrow TRACKER}$

Image Reg. ($F_{CT\leftarrow US}$)

Surface Reg. ($F_{CT\leftarrow SURFACE}$)

3D Tracker

Real-Time Vessel Segmentation

Tracked US

Video Tracking

US Vessels

Vessel Reg. ($F_{CT\leftarrow VSL}$)
Digital Test Bed

CT Image

Probe Orientation

Ultrasound Simulator

Simulated Tracker Error

Rigid Transform

Synthetic US Image

CT Surface Model

Tracked Range Data

Registration Algorithm

\( F_{CT \leftrightarrow TRACKER} \)

Simulated Real-Time US Dataset

Ultrasound Simulator to be provided by Siemens/TUM*

A Clinical Application

• Neo-adjuvant chemotherapy monitoring of breast cancer patients
  – Current collaboration involving MUSIIC lab (Emad Boctor) and surgeons from Johns Hopkins
  – Clinical Situation: Patients confirmed (by biopsy) to have cancer are treated with chemotherapy to shrink the tumor prior to surgical resection of the tumor (lumpectomy)
  – Clinical Goal: evaluate effectiveness of patient-specific treatment
    There is growing awareness in the medical field that predetermined regimens are not well suited for cancer treatment due to the many qualities unique to each patient that affect the optimal treatment plan.
  – Study Protocol:
    • Initial visit: patients receive extensive imaging: MRI, PET/CT, ultrasound
    • Monitor and adjust the treatment through several follow-up visits where additional imaging is acquired to assess the patient’s condition
  – Technical Need:
    • Coregister the various imaging modalities from a single visit to assess patient condition at each visit
    • Coregister imaging across visits to assess rate of change in patient condition
A Clinical Application

Physical System
- Polaris Tracker
- Structured Light System With Stereo Video
- US Probe
- Reference Frame
- Breast of Patient

Registration Model
- Time-Stamped Data
- Surface
- B-Mode US
- Elastography
- X, Y, Z Tracking Data
- Surface Model of Breast CT
- Breast CT
- Registration Algorithm $F_{CT \leftarrow TRACKER}$
A Clinical Application

• How this applies to my work:
  – Data is acquired from many sources
    • PET/CT, Ultrasound, Surface Data, MRI
    • Features on breast surface
  – Doesn’t have real-time component, but has the potential to apply a real-time system to guide the eventual surgery
    • Could also run real-time component off-line, using re-runs of saved timestamps for each piece of data
Status

• Developing software framework to enable the various types of registration required:
  – ITK: image registration routines
    • Modifying to support simultaneous registration of a collection of images rather than single images
  – Slicer4: for visualization, I/O, and human interface to the system
    • Learning how to integrate loadable modules with ability to provide visual feedback as registration progresses
  – Surface Registration
    • Implemented a fast C++ version of Coherent Point Drift (an algorithm for statistical point set registration)
Status

• Studying Bayesian methods and machine learning algorithms
Acknowledgements

• Advisors & Mentors
  – Russell Taylor (JHU)
  – Emad Boctor (JHU)
  – Brad Wood (NIH)
  – Sheng Xu (NIH)
  – Ankur Kapoor (NIH)

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  – NSF Graduate Research Fellowship
  – Graduate Partnership Program (NIH, Clinical Center)
  – Intuitive Surgical, Inc. Research Grant (JHU)
Summary of Proposed Contributions

• Develop an algorithm for dynamic patient-CT registration.
  – hybrid image/surface data
  – historical data

• Build navigation system to test/validate the registration algorithms developed.

• Improve real-time performance of the navigation system (GPU implementation, motion tracking, etc).

• Other Possible Contributions
  – Build laparoscopic navigation system suitable for clinical use
  – Incorporate additional forms of sensing to help registration (blood vessels segmentation, video tracking, etc.)
Clinical Navigation System

EM Tracker

F_{CT \leftarrow US} (Image Reg.)

CT

Kidney

F_{CT \leftarrow SL} (Surface Reg.)

Structured Light

Ablation Needle

Abdominal Wall
Phantom Test Bed

- Optical Tracker
- Structured Light Stereo Vision System
- US Probe
- Multi-Modality Phantom
- Lesions

$F_{CT \leftarrow SL}$ (Surface Reg.)
$F_{CT \leftarrow US}$ (Image Reg.)
Clinical Test Bed

Structured Light Stereo Video System

Optical Tracker

US Probe

Breast of Patient

CT of Breast

$F_{CT \leftrightarrow SL}$ (Surface Reg.)

$F_{CT \leftrightarrow US}$ (Image Reg.)
# Test Bed Navigation System

- Estimated Build Cost

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<thead>
<tr>
<th>Item</th>
<th>Description</th>
<th>Qty</th>
<th>Unit Cost</th>
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<tbody>
<tr>
<td>Camera</td>
<td>Point Grey 1.4MP FireWire</td>
<td>2</td>
<td>$925</td>
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<tr>
<td>Lens</td>
<td>Edmund Optics, 8.5mm focal length megapixel lens</td>
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<td>Projector</td>
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<td>Raw Materials</td>
<td>Acrylic sheets, hardware, etc.</td>
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<tr>
<td>Accessories</td>
<td>Cables, etc.</td>
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<td>$20</td>
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<td><strong>TOTAL</strong></td>
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<td><strong>$3,010</strong></td>
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## Projected Timeline

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<th>Activity</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
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<tbody>
<tr>
<td></td>
<td>Apr-Jun</td>
<td>Jul-Sept</td>
<td>Oct-Dec</td>
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<tr>
<td>Build System Framework</td>
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<tr>
<td>Software framework for registration</td>
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<tr>
<td>Test bed navigation system</td>
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<td></td>
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<tr>
<td>Hybrid Registration with Digital Phantom</td>
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<tr>
<td>Develop hybrid registration approach with image/surface metric</td>
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<tr>
<td>Hybrid registration case study</td>
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<tr>
<td>Registration with Historical Data</td>
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<tr>
<td>Develop registration approach incorporating historical data</td>
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<tr>
<td>Historical registration case study</td>
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<tr>
<td>Accelerated Registration</td>
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<tr>
<td>GPU Implementation</td>
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<td>Other final work (tracking, etc.)</td>
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<tr>
<td>Accelerated registration case study</td>
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</table>

**MERIT**

**MUSIIC**

**NSF**

**ERC | CISST**
Dependencies

• Personal Salary & Tuition
  – Present to Aug. 2012
    • NIH GPP: personal salary, health insurance, 5k tuition/yr
    • MUSIIC Lab (Emad Boctor): remaining tuition (~4k per year)
  – Sept. 2012 to 2014
    • NSF Fellowship: personal salary, health insurance, tuition

• Advisors
  – JHU: Russell Taylor, Emad Boctor
  – NIH: Dr. Brad Wood, Sheng Xu

• Additional Coursework
  – Topics related to Bayesian Learning & Stochastic Models
Dependencies

• Test Bed Navigation System
  – Structured Light System (~3k to build)
  – Tracker: Polaris optical tracker
  – Ultrasound machine & tracked probe

• Phantoms
  – Kidney phantoms: avail from MUSIIC lab
  – Torso phantoms: avail from NIH
  – NIH offered to purchase others as needed

• Computer
  – Laptop from NIH
  – Desktop from JHU

• High Performance GPU
  – Avail from MUSIIC Lab & NIH
Dependencies

• Clinical Laparoscopic Test Bed (Not Essential)
  – Lap structured light system: not avail; may require much engineering effort + time to build
  – Tracked lap US probe: avail at NIH
  – Tracker: new NDI Aurora avail at NIH; older EM trackers avail at JHU

• Competition
  – Robarts Research Institute
  – Vanderbilt University
  – Harvard Medical School + MIT
  – Imperial College, UK
  – University of Lubeck, Germany
Why So Many Different Data Sources?

- Problems for Ultrasound-CT image registration:
  - Local minima (small capture region about the optimal solution)
  - 2D-3D registration is not well-constrained (weak gradient in some directions)

- Need additional information to constrain the registration (i.e. surface data, historical information, etc.)
Surface + Image Registration Study

- Goal: study the capture range of the globally optimal solution for independent surface and image registration using single US image
- Registration ground truth:
  Fiducial (for surface); manual (for image)
US/CT Image Registration Study

Transverse

Coronal

Sagittal

<table>
<thead>
<tr>
<th>CT</th>
<th>US</th>
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</thead>
<tbody>
<tr>
<td>X</td>
<td>Depth</td>
</tr>
<tr>
<td>Y</td>
<td>Elevation</td>
</tr>
<tr>
<td>Z</td>
<td>Lateral</td>
</tr>
</tbody>
</table>
US/CT Image Registration Results

Translation

Rotation
TOF/CT Surface Registration Study
Example of Typical Result

Note: 2x scaling in anterior/posterior direction

Fiducial Position Error
Avg: 10.8mm, Min: 8.6mm, Max: 12.2mm
Summary of Registration Study and Relationship to Current Work

• 2D Ultrasound Image registration:
  – Asymmetrically constrained along different DOFs
  – Small capture range: 15-25mm and > +/- 15 deg
    (for well-constrained directions)

• Time-of-Flight Surface Registration:
  – Large capture range; weak termination condition
  – Large calibration & registration errors
    • Noisy TOF data

• Hypothesis: (Current Work)
  – **Hybrid image/surface registration** with historical data will help address the weaknesses in each registration method
  – **Accurate 3D surface model** (recovered from structured light stereo vision range imaging, etc.) will improve surface registration