From Image Guidance to Image Analytics for Precision Spine Surgery

Jeff Siewerdsen, PhD

John C. Malone Professor of Biomedical Engineering
Computer Science, Radiology, and Neurosurgery
Vice-Chair for BME Clinical and Industry Translation
Johns Hopkins University
**Rate of Spine Surgery Soars**

- **3 M**
  - Spinal fusion surgery/year

- **$12 B**
  - Market

- **32%**
  - Increase in procedures between 2004 and 2015

- **73%**
  - Increase in procedures between 2004 and 2015 in ages above 65

- **152%**
  - Increase in cost of care between 2004 and 2015

- **13%**
  - Patients with no improvement in leg pain

- **19%**
  - Patients with no improvement in back pain

- **16%**
  - Patients with no improvement in function

- **25%**
  - Overall 90-day readmission rate

- **10%**
  - 30-day unplanned readmission rate

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**Spinal fusions serve as case study for debate over when certain surgeries are necessary**

**The Washington Post**

**Why ‘Useless’ Surgery Is Still Popular**

Tools for Image-Guided Surgery

Automatic Planning
- Statistical atlas / Active shape model (ASM) registration

Deformable Image Registration
- Multi-modality (CT and MRI)

Target Localization
- Vertebrae labeling

Surgical Device Localization
- Implants (rigid and deformable) and robotics

Re-Purposed to Image Analytics at Scale
- High-level feature extraction
- Input to predictive models, clinical decision support (CDS)
Automatic Surgical Planning

**Surgical Navigation**
Mainstay for spinal MIS
Free-hand screw placement

**Robotic Assistance**
Planning is *required* for robot positioning

**Quality Assurance**
Analyze deviations between planned and delivered
Automatic Surgical Planning

→ Automatic, High-Level Image Feature Extraction

Definition of a “reference plan”
Patient-specific planning
Surgeon-specific prefs via atlas
Post-operative QA
Retrospective analysis, correlation with outcomes
Deformable Image Registration

CT-CBCT

Demons

\[ \dd = \frac{2(m-f)(\nabla f + \nabla m)}{k(m-f)^2 + |\nabla f + \nabla m|^2} \]


MRI-CT

MIND Demons

\[ m_{i,j}(x) = c \exp \left( -\frac{d(l, x, r_i)}{V(l, x)} \right) \]

Reaungamornrat et al., IEEE-TMI (2016) and Med Phys (2017)

Free-Form Deformation

MI B-Spline + Rigid Constraint

\[ MI - \sum_x c_x \{\lambda_A A + \lambda_P P + \lambda_O O\} \]

Deformable Image Registration

**Input**
Images to Register

**Output**
Displacement Vector Field

**U-Net Architecture**
SVF-Net
Supervised Training
TensorFlow, Adam Optimizer

Deformable Image Registration

→ Suitability to Deformable Registration in Large Datasets

Widely varying imaging protocols (dose, noise, resolution)

Matching statistics is optimal... but a diverse training set yields a robust single network.
Target Localization

Automatic Vertebral Labeling in CT

Relatively simple networks for object detection in 2D – YOLO

Combine slice-by-slice detections

Alternatively, 3D CNN – requires ~100x more memory

Deeper network to improve accuracy – Inception V2 Network

42 layers deep (combines 7x7, 5x5, and 3x3 convolutions) F-RCNN

→ Ortho-2D (parallel orthogonal slice detections)

1. Redmon et al, CVPR (2016)

Levine et al., SPIE Medical Imaging (2019)
Target Localization

Localization Accuracy
N = 51 patients (115 radiographs)

Projection Distance Error, PDE (mm)

FR = 49%
FR = 15%
FR = 27%
FR = 0%

Similarity Metric
GI GC GS GO

Target Localization

→ Automatic Spine Labeling
   Suitability to large datasets
   Determination of levels treated
   Initialization of planning / registration

→ Automatic GSA
   A strong determinant of clinical outcome
   High-level feature extraction:
   Preoperative GSA
   Change (preop-to-postop) GSA
Device Localization

\[ \hat{u} = \arg \max_u \sum_\theta GC \left( P_\theta, \int_{\tilde{r}} C(u) d\tilde{r} \right) \]

High-Level Feature Extraction

Automatic determination of breach

\[ \Lambda_{\text{screw}} \cap \Lambda_{\text{vertebrae}} \]

Number and type of screws
Planned vs delivered position

\[ \Delta_{r,\phi} = \hat{d}_{\text{screw}} - \hat{d}_{\text{plan}} \]
Spine Surgery Outcomes Prediction

Automated Extraction of High-Level Image Features

- Level detection
- Spinal curvature
- Implant placement
- Deviation from ideal trajectory ...

Clinical / Demographic Data

- PROMIS Domains
  - Physical Health
    - Function/Disability
    - Symptoms
  - Mental Health
  - Social Health

Patient Demographic Data (EHR)

PROMIS-29

Predict Outcome / Decision Support

Patient Selection
Surgical Planning
Rehabilitative Path

Preop Atlas Registration
Reference Trajectories
Spinal Labeling

GSA
C7S1 SVA
PT VMA

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Spine Surgery Outcomes Prediction

Classifier: $f(x) = \sum_{t=1}^{T} \alpha_t h_t(x)$

Weights: $\alpha_t = \frac{1}{2} \log \frac{1 - \epsilon_t}{\epsilon_t}$

Classification Error:

$\epsilon_t = \sum_{n=1}^{N} d^{(t)}_n I(y_n \neq h_t(x_n))$

- $y_n$: true outcome variable
- $I$: indicator function
- $d^{(t)}_n$: weight of the observation $n$ in $t$

Boosted Decision Tree

- BMI<27 / BMI>27
- LL<60 / LL>60
- L5 C>-20 / L5 C<-20
- ~Smoking / Smoking

Ada-Boost classifier
- N classes = 2
- Learning cycles = 30
- Learning rate = 0.1
- K-fold cross validation

N samples = 84

Spine Surgery Outcomes Prediction

12 Months (mJOA Function)

- **SpineCloud-3M**
  - AUC = 0.82
  - (CI\(_{95}\) = 0.70 – 0.93)

- **SpineCloud-0M**
  - AUC = 0.69
  - (CI\(_{95}\) = 0.54 – 0.82)

Demographics
- AUC = 0.32
- (CI\(_{95}\) = 0.19 – 0.46)

**Feature Importance**

- SpineCloud-0M (12-mo mJOA)
  - LC pre T12:
  - IVD 0m L4:
  - IVD 0m L3:
  - EP 0m T11:
  - EP 0m S1:
  - IVD 0m L2:
  - EP pre S1:
  - LL 0m:
  - Age:
  - LC 0m L1:

10^-5
New role for image registration / analysis methods developed for high-precision IGS

High-level feature extraction → Input to predictive models

A New “Precision” Paradigm for Surgery

Geometric precision
  Millimeter targeting via navigation, robotics, etc.

Precision medicine
  Patient-specific feature guide optimal treatment pathway

Explainable model → Actionable CDS

Features that cannot be derived from demographics alone
  E.g., N levels to treat, targeted degree of curvature

Identify features that could improve trajectory, outcomes
Guide patient selection, planning, and rehabilitative pathway
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