LEARNING FOR 2D-3D IMAGE REGISTRATION IN SURGERY

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Abstract

Registration of pre-operative planning data to intra-operative imaging is an integral step of the image-guided surgery. Limited image quality, obstructing surgical devices and high accuracy requirements challenge the state of the art in 2d-3d registration. The recent success of **deep learning** raises the hopes that it can help to tackle these challenges. This poster presents **strategies for data collection** in this scenario and a learning-based method for 2d-3d registration. The method achieves a **low failure rate with 4.1%** of the cases with a TRE over 1cm.

Challenges

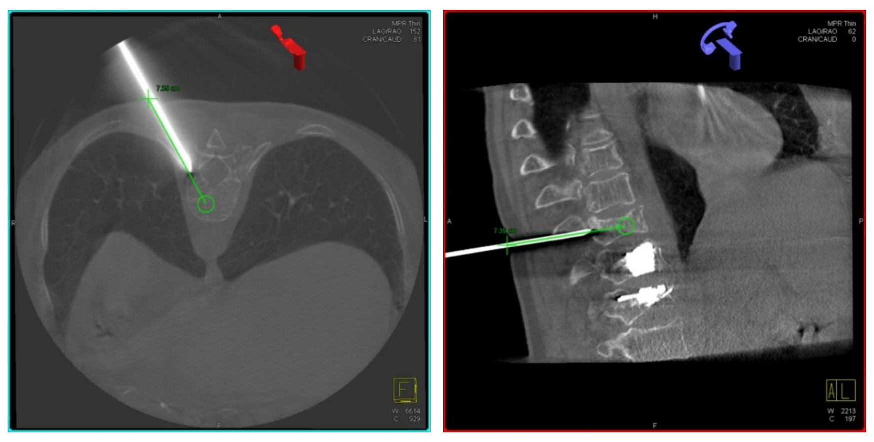


Fig.1: Application example: guidance of pedicle screw placement

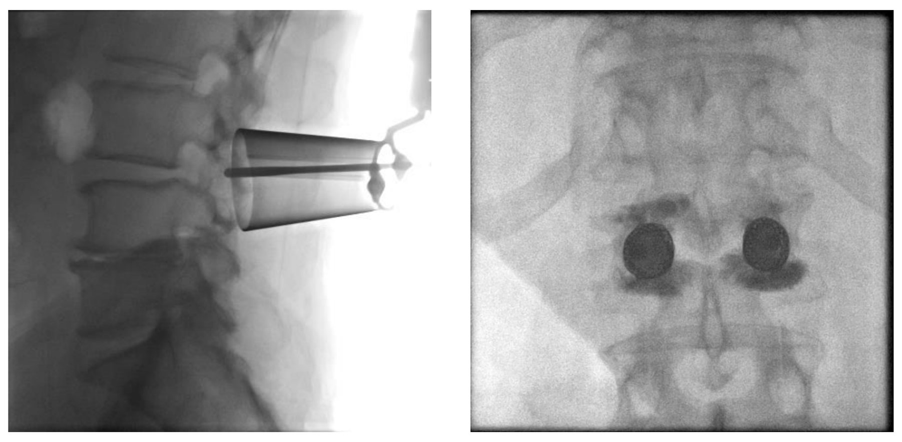


Fig.2: Metal in 2d, deformation between 2d and 3d, and limited field of view

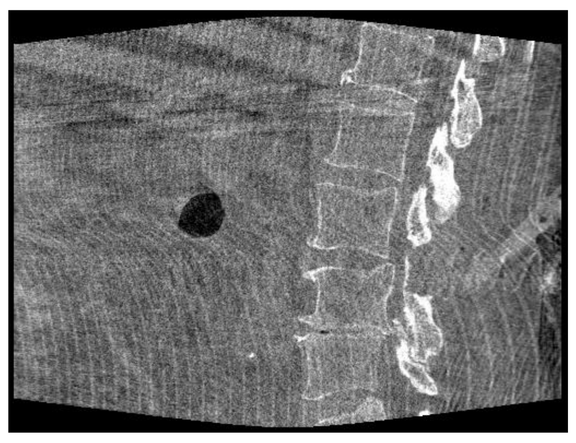


Fig.3: Metal artifacts due to surgical tools

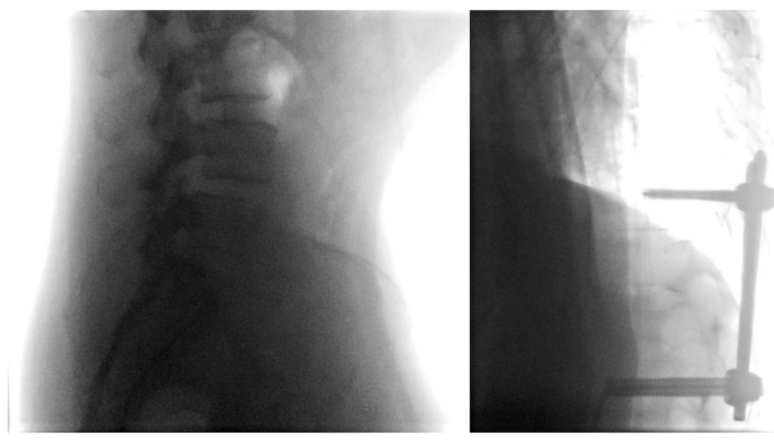


Fig.4: Low contrast and overexposure

Methods

Classical 2d-3d registration [1,2]:

- Optimizing **similarity metric** f computed between X-ray and DRR
- 3d update using point-to-plane correspondence of features
- **Heuristics** to initialize and to increase capture range

Learned agent (AI) [3,4]:

Agent trained by supervised deep reinforcement learning. Direct optimization of target registration error (TRE) during training. **Data-driven** approach to handle common challenges.

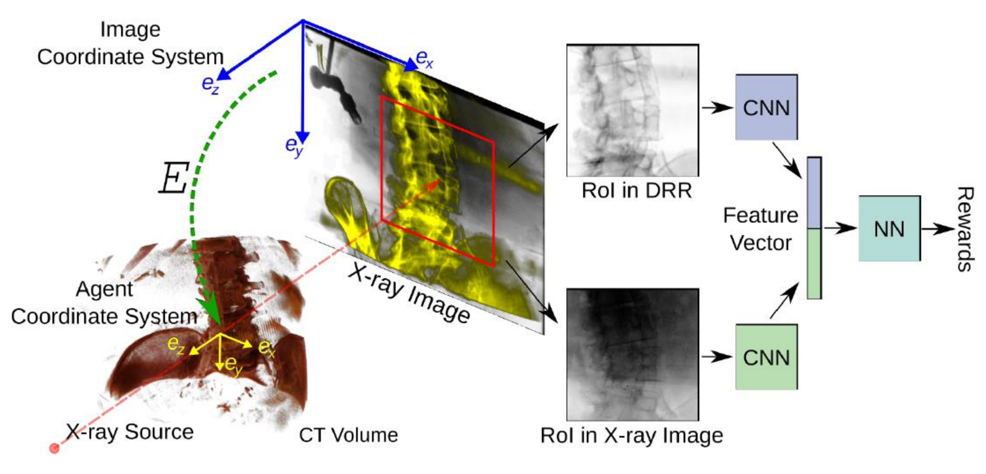


Fig.8: Design of registration agent

[1] Otake et al.: *Automatic localization of vertebral levels in x-ray fluoroscopy using 3d-2d registration: a tool to reduce wrong-site surgery*. PMB, 2012

[2] Wang et al.: *Dynamic 2-d/3-d rigid registration framework using point-to-plane correspondence model*. IEEE TMI, 2017

[3] Miao et al.: *Dilated FCN for multi-agent 2d/3d medical image registration.* AAAI, 2018

[4] Toth et al.: *3D/2D model-to-image registration by imitation learning for cardiac procedures.* IJCARS, 2018

Data Collection

Requirements:

A dataset for registration requires a **3d CT/CBCT** of the spine together with **2d X-ray** images from multiple angles with a **calibrated projection geometry** and a **ground truth registration** between the 3d and 2d images. There are multiple options to get such data.

Simulation from CT (~1000 cases):

From a 3d CT, the X-ray images can be simulated, with the advantages of **accurate ground truth** and **easy availability**. This constitutes a simplified registration problem, as there are **no deformations** between 3d and 2d and the **images are unrealistic**.

CBCT and corresponding projection images (~300 cases):

A CBCT images is generated from X-ray projection images. The images are **intrinsically registered** and accurately calibrated. The registration problem is still too simple, as there is no content mismatch between 2d and 3d.

Retrospective collection of clinical images (~50 cases):

This data is the **most realistic** w.r.t. image quality and content, but the **availability is limited** as X-ray images are not routinely stored. There is also **no calibration** of the projection geometry and **no ground truth registration.**

Cadaver Experiments

Cadaver experiments enable to collect realistic clinical images with accurate calibration of the projection geometry and ground truth registration. This requires a specialized **hardware setup**. A stationary robotic C-arm (Fig.5) is calibrated for 3Ds and for fixed 2d image acquisition positions, which are approached with the repeatability of the robot. A X-ray translucent reference (Fig.6a) is attached to the vertebra of interest and is tracked by an **optical tracking system** (OTS) (Fig.7) to provide the ground truth. The coordinate systems are registered using point-based registration of a hybrid OTS/X-ray marker (Fig.6b).
The **final accuracy** of the setup determined by robot repeatability, OTS error, and calibration errors is in the range of **0.5 mm**.
The experiments are performed in the MERI facility in Memphis, USA.

Fig.5: Robotic C-arm

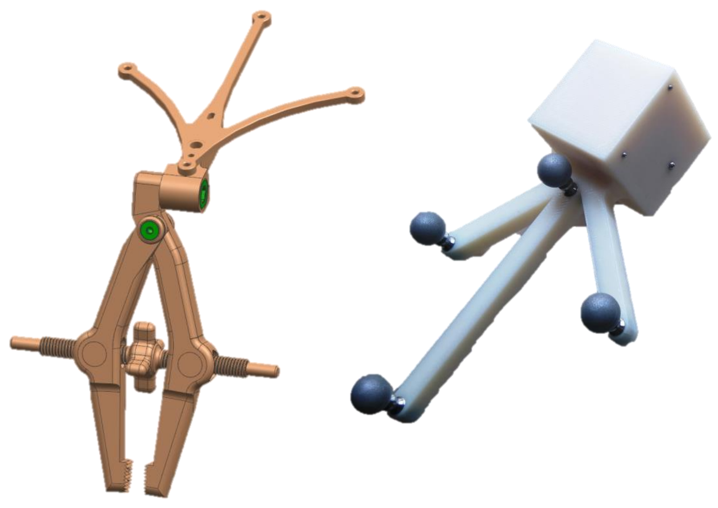
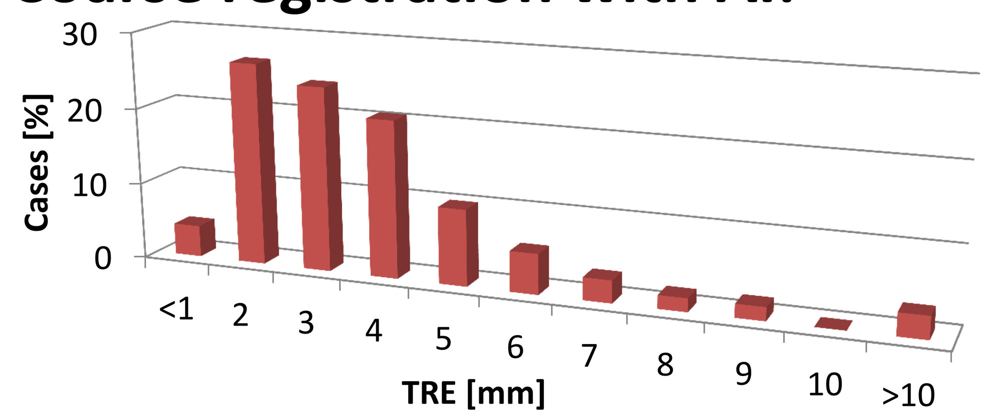


Fig.6: Optical markers

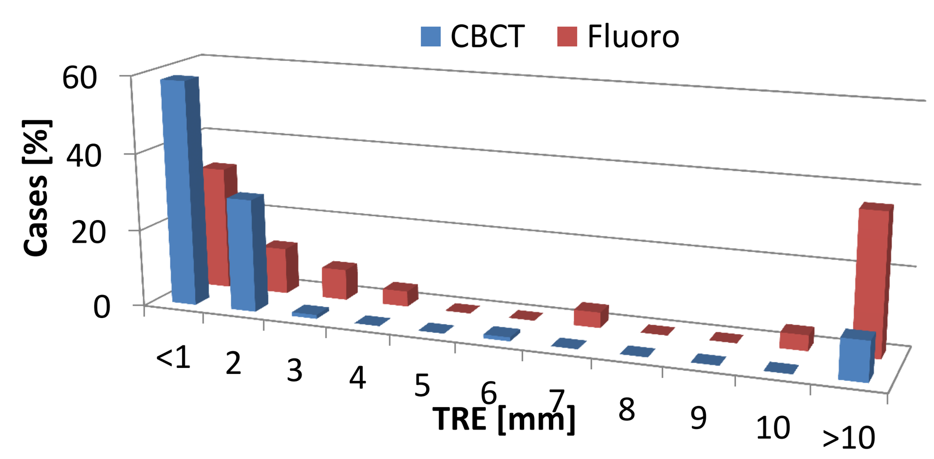
Fig.7: Optical tracking

Preliminary Results

Coarse registration with AI:



Refinement with classic 2d-3d:



Conclusion:

AI registration is robust to local minima and image variations. For fine registration with low capture range, classical registration is still better.