Monitoring Surgical Activities with Artificial Intelligence: Toward a Surgical Control Tower

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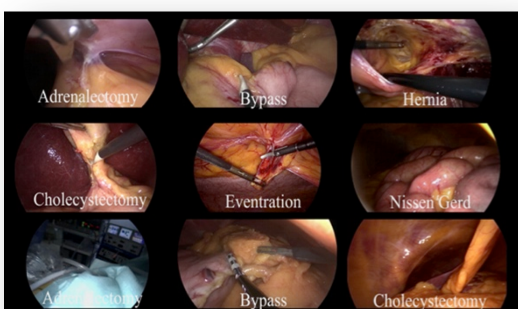
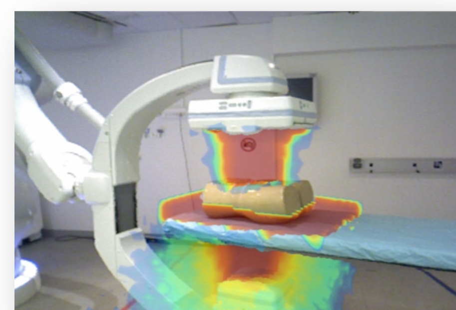




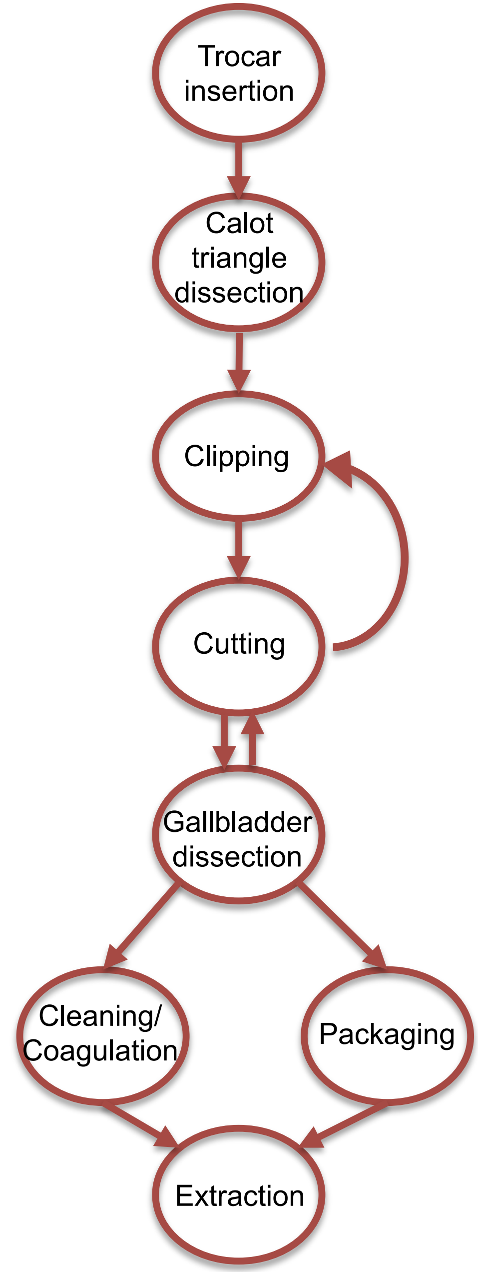
April. 23, 2019

Outline

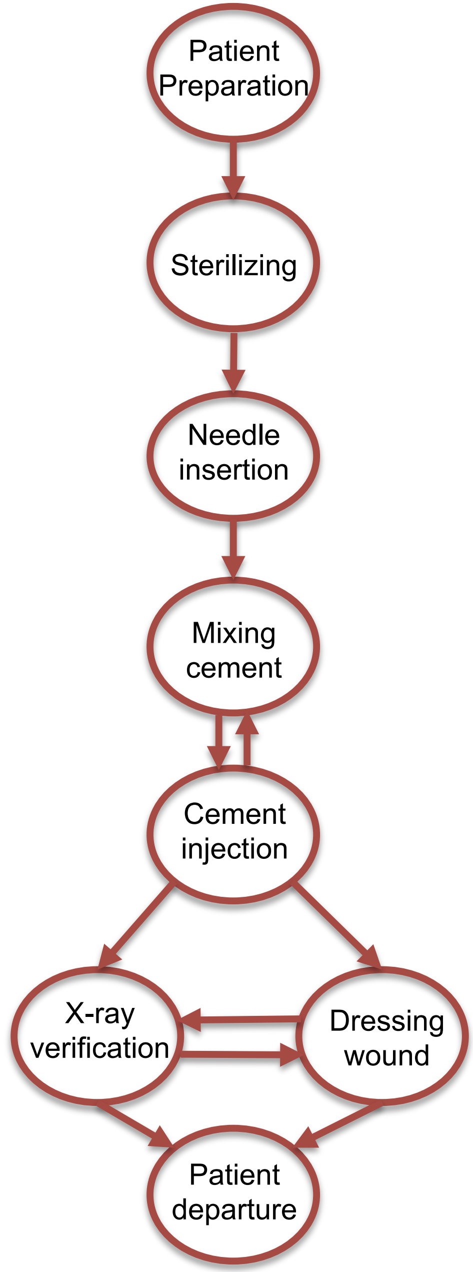
① **Surgical control tower: challenges and opportunities**

② **Examples of clinical applications**

③ **Ongoing research questions**

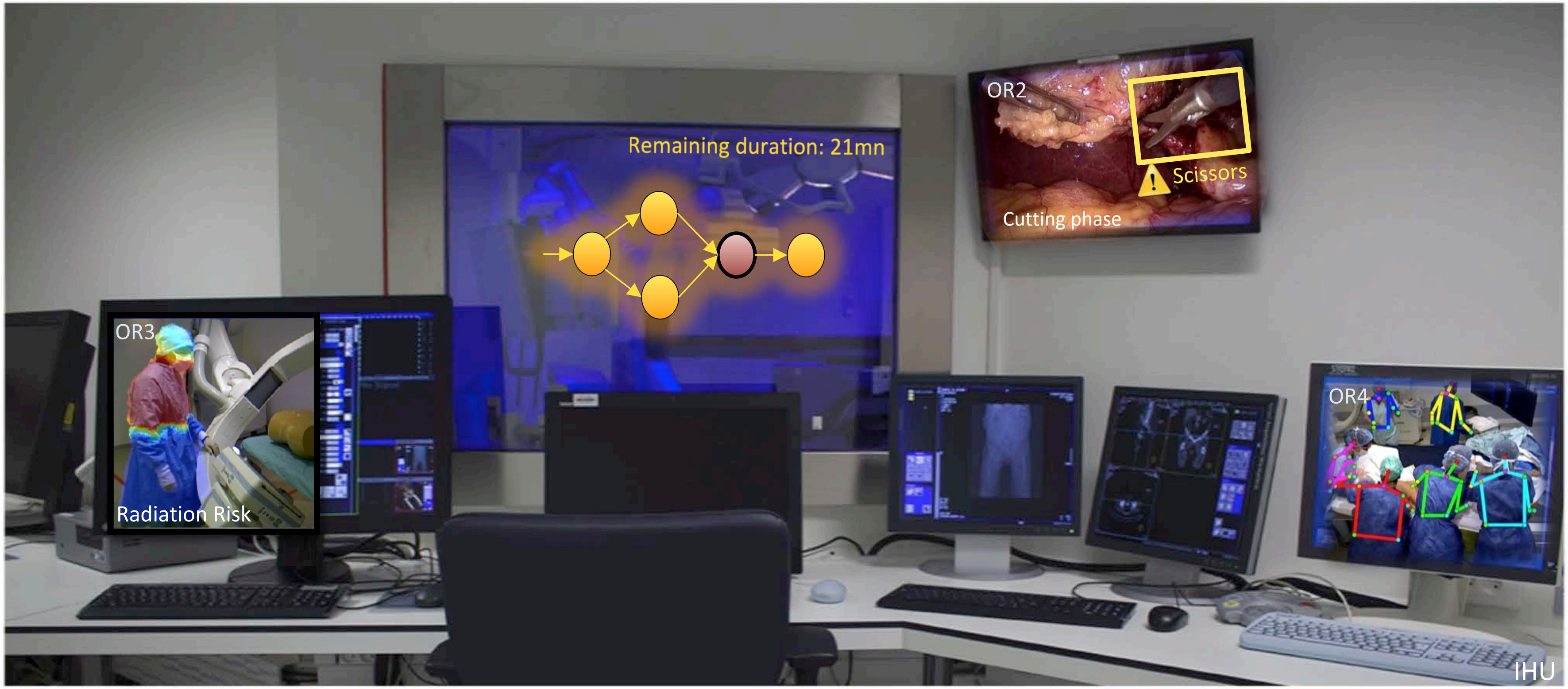


Workflow (cholecystectomy)

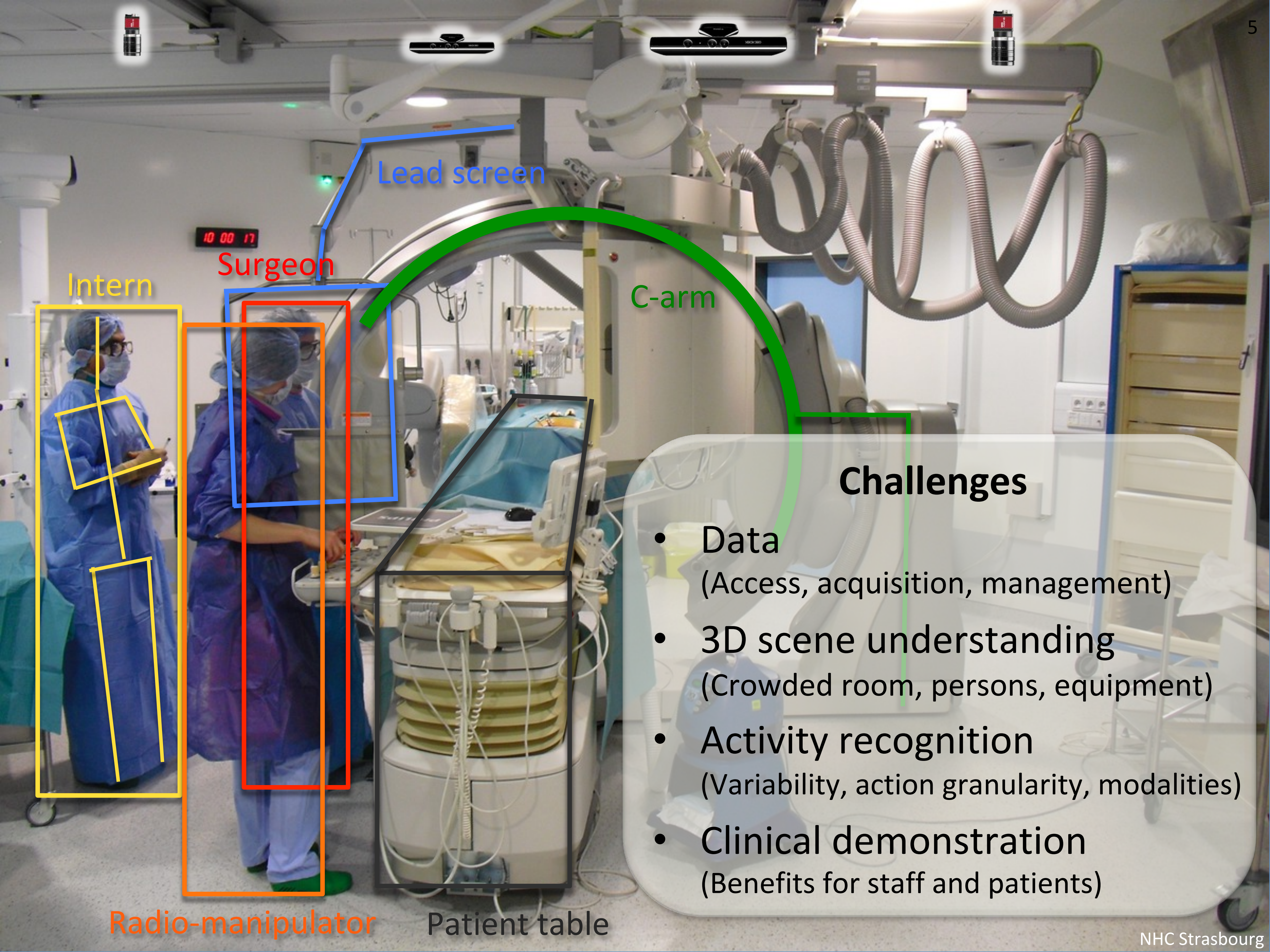


Workflow (vertebroplasty)

Surgical « Control Tower »



- ⟶ **Up-to-date OR status anytime anywhere**
- ⟶ **Safety monitoring and anomaly detection**
- ⟶ **Automation (notifications, data indexing)**
- ⟶ **Context-aware user interfaces**
- ⟶ **Workflow optimisation & training**



Challenges

- Data
  (Access, acquisition, management)
- 3D scene understanding
  (Crowded room, persons, equipment)
- Activity recognition
  (Variability, action granularity, modalities)
- Clinical demonstration
  (Benefits for staff and patients)

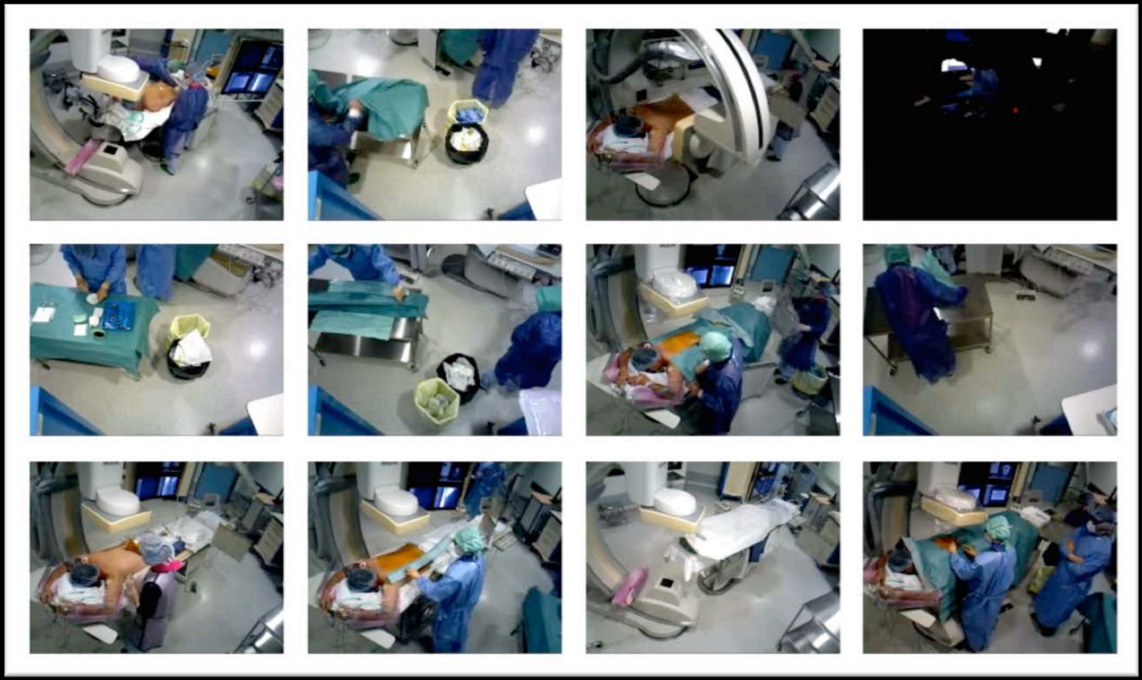
Opportunities

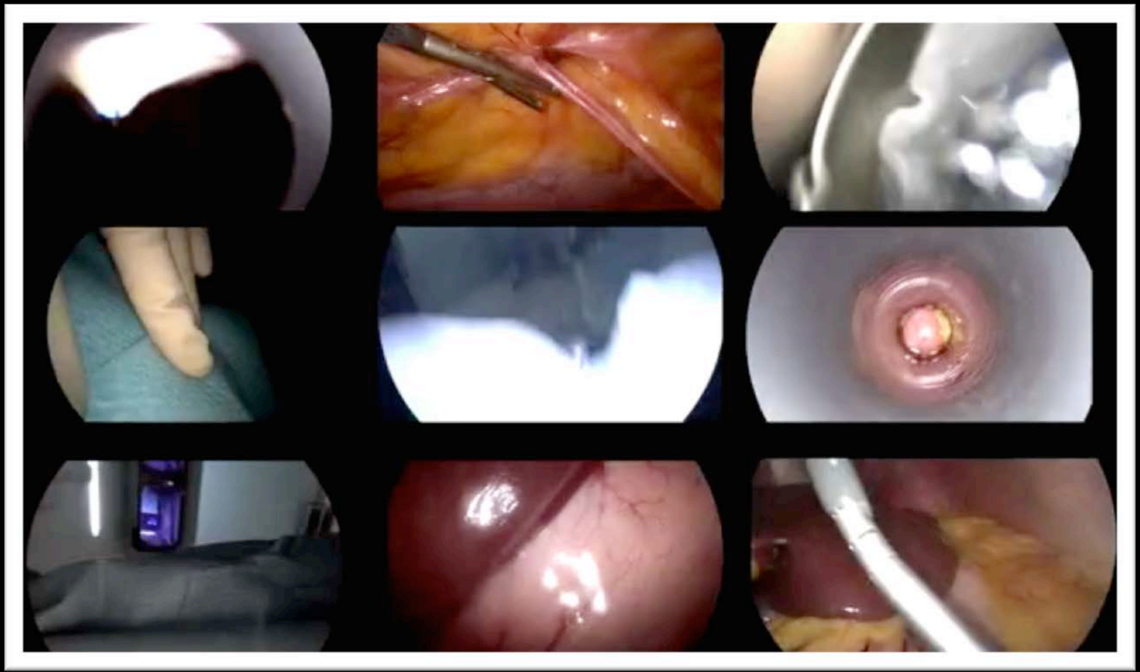
- Live-signaling systems
  - Jung & Grantcharov, *The Operating Room Black Box: A Prospective Observation Study of the Operating Room*, JACS 2017
  - 129 recordings: disruption occurs once every 75 seconds

- Monitoring
  - Levy et al. *Rapport Annuel de l'Observatoire des risques médicaux*, 2014
  - About 1% of surgeries contain a preventable serious adverse event

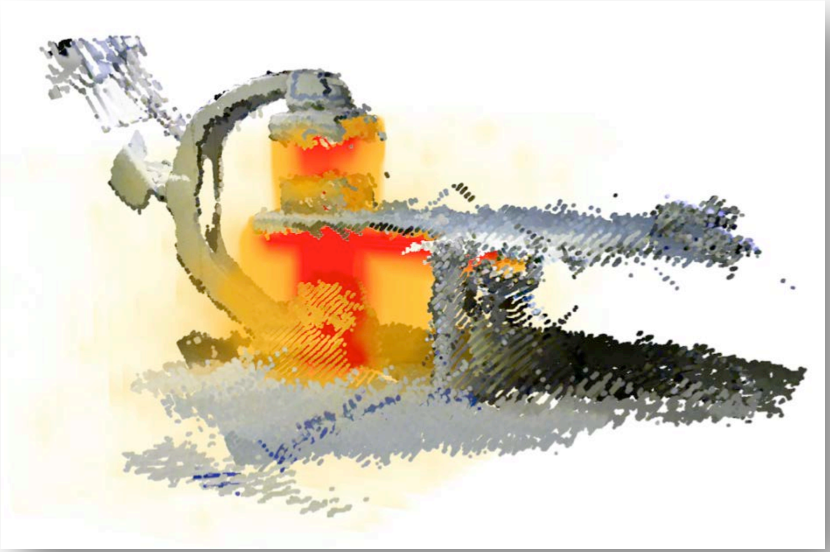
- Context-aware assistance
  - Birkmeyer, *Surgical Skill and Complication Rates after Bariatric Surgery*, NEJM 2013
  - 3 times higher complication rate for bottom quartile of surgical skill

- Safety checkpoints
  - Nijssen et al., *Complications After Laparoscopic Cholecystectomy: A Video Evaluation Study of Whether the Critical View of Safety was Reached*, WJS 2015
  - According to operative notes CVS obtained in 80 % of cases / According to video reviewers CVS attained in only 10.8 % of cases





X-ray Safety Monitoring (XAware)



Clinical partners: IHU Strasbourg & Nouvel Hôpital Civil (Department of Interventional Radiology)

Motivation: Radiation Exposure in the OR

- Increasing exposure of clinical staff and patients to potentially harmful ionizing radiation during MIS

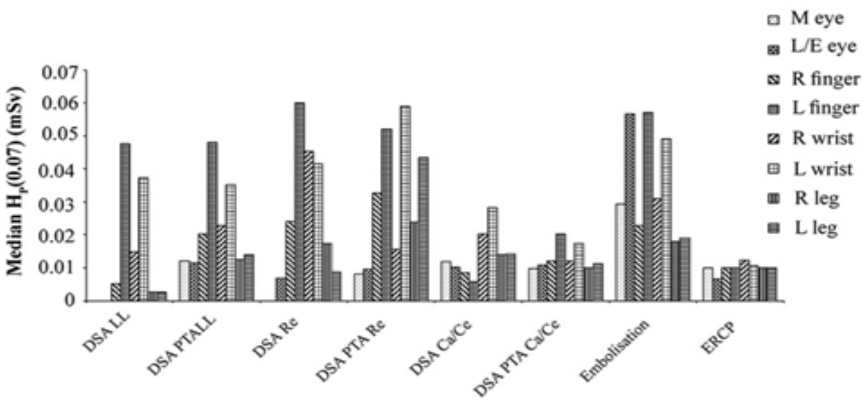
- Long-term exposure in unprotected body-parts can lead to negative effects:
  - Lens injuries
  - Cataracts
  - Cancers

- Current protective measures:
  - Lead aprons
  - Thyroid collars
  - Lead screens
  - TLD dosimeters

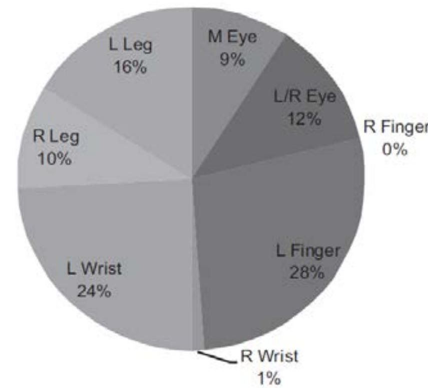
Miller DL. et al., *Interventional Radiology: reducing radiation risks for patient and staff,* JVIR 2009

Understanding Radiation Propagation in the OR

ORAMED (EU FP7) measurement campaign 2011 [1]

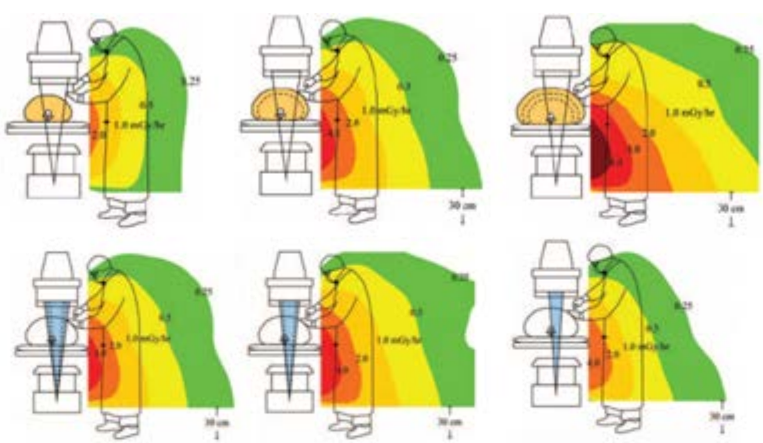


Body-part doses per procedure



Position of the maximum dose

Scattered radiation fields are complex and high risk areas are not easily predictable



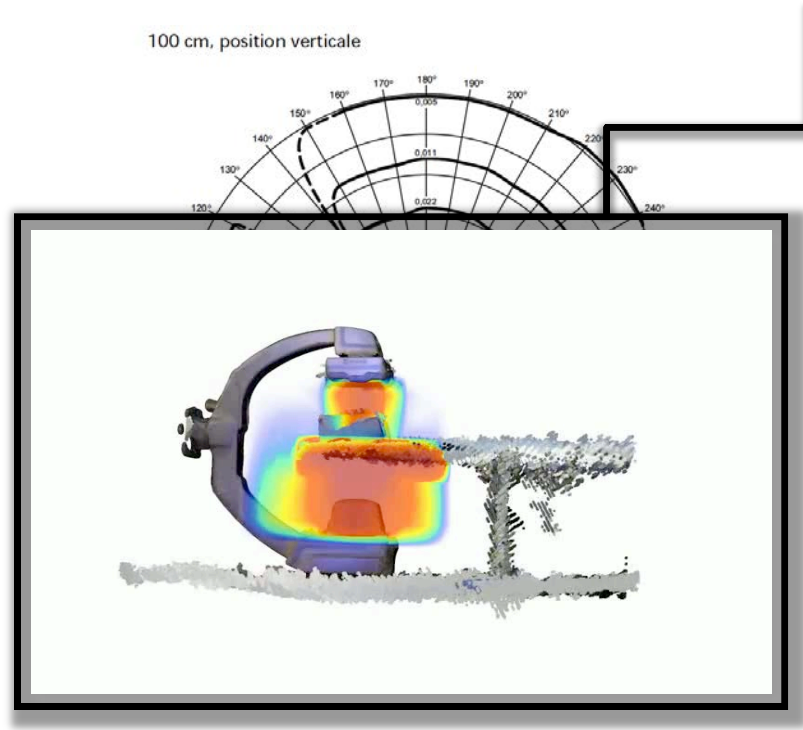
Influence of the patient's size

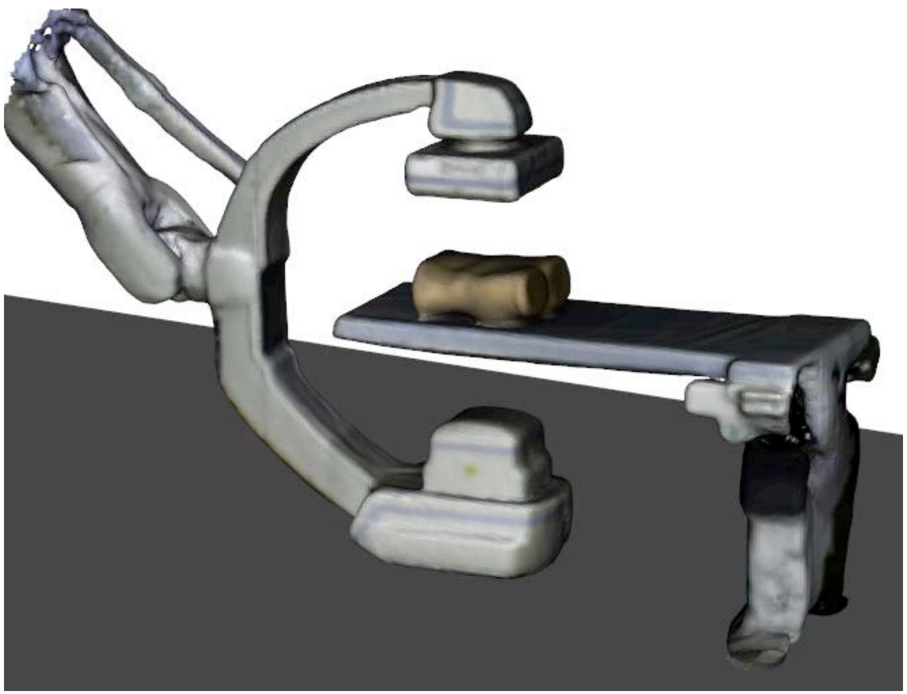
Influence of the X-ray FOV

[1] Carinou E. et al., *Recommendations to reduce extremity and eye lens doses in interventional radiology and cardiology,* Radiation Measurements 2011

XAware’s Vision

Personal dosimeter

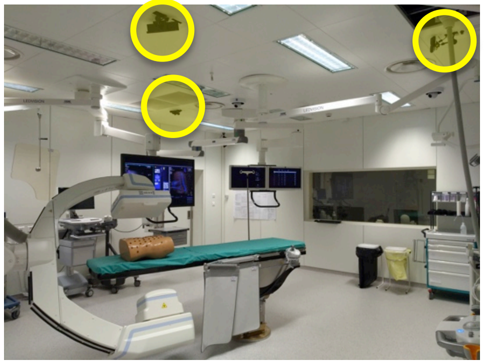




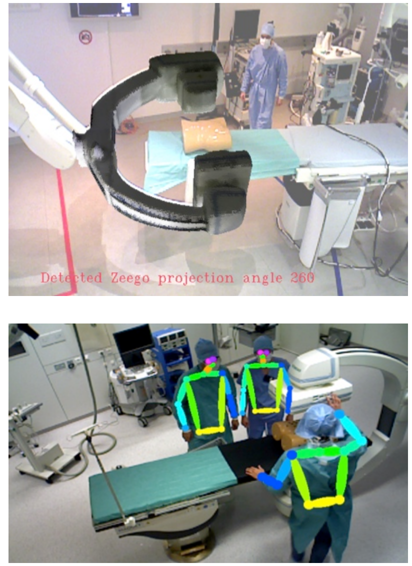
- 3D AR visualization for training
- Real-time feedback
- Statistics per body part and activity
- Workflow & room optimization

Loy Rodas et al, **3D Global Estimation and Augmented Reality Visualization of Intra-operative X-ray Dose**, MICCAI 2014 (Oral)

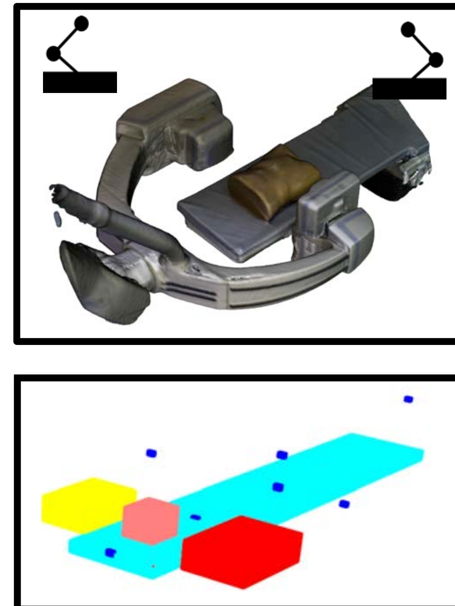
Approach



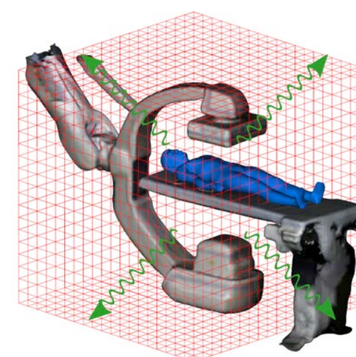
Multi-RGBD Camera Setup



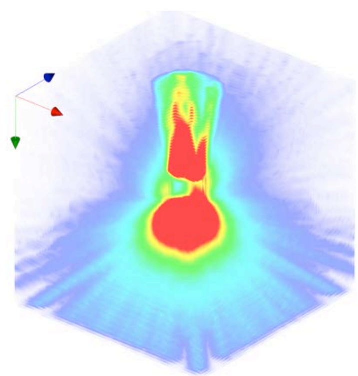
3D Room Understanding



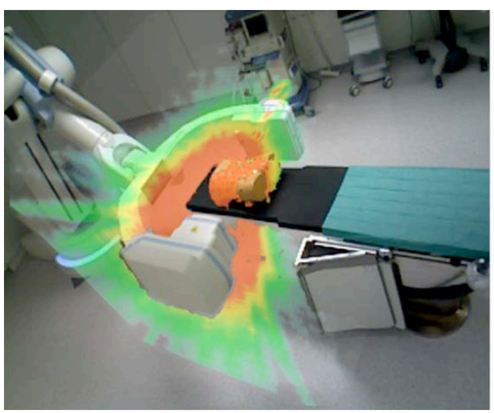
Virtual Modeling



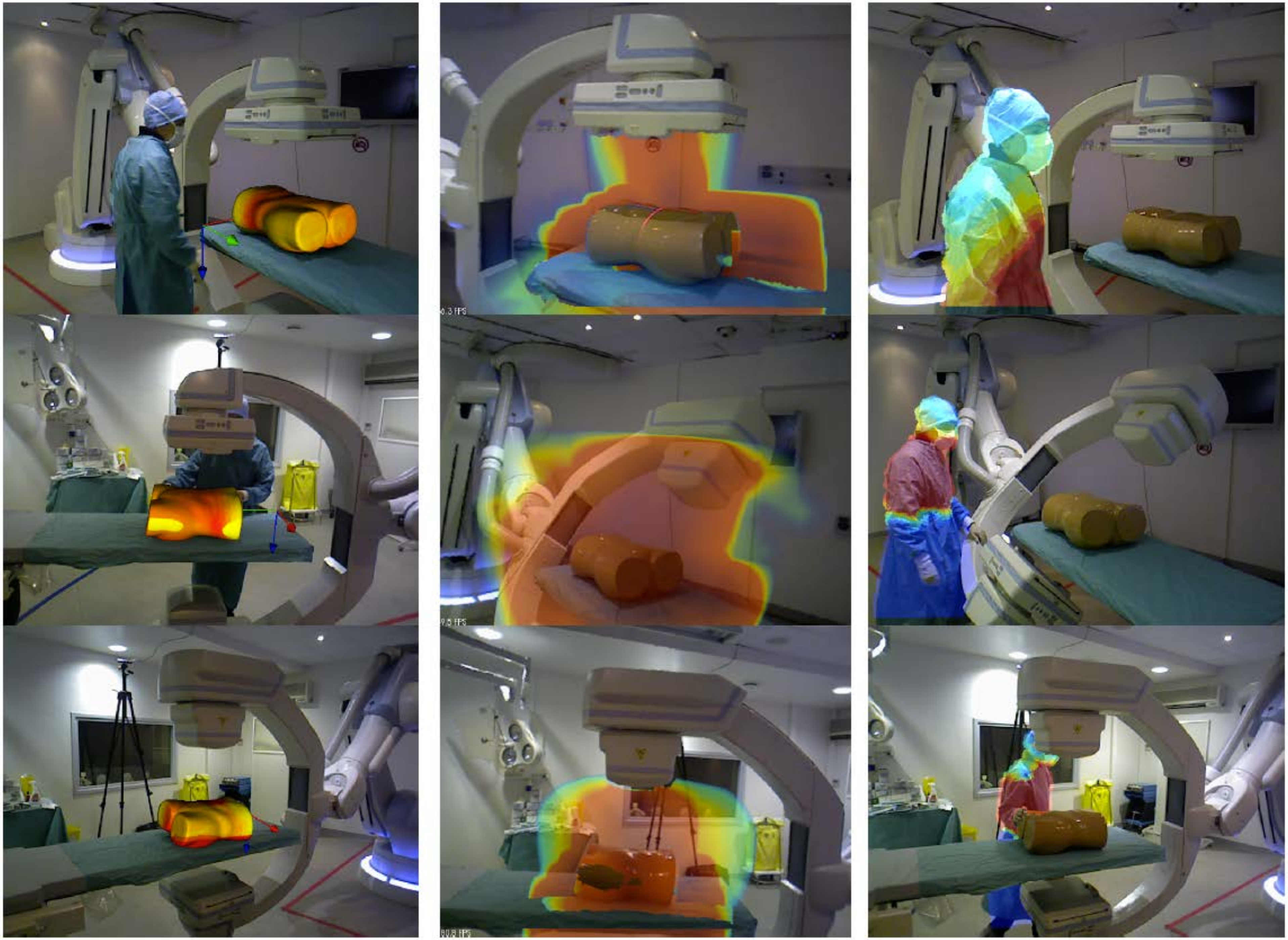
Monte Carlo Simulation



3D Dose Map



Augmented Reality

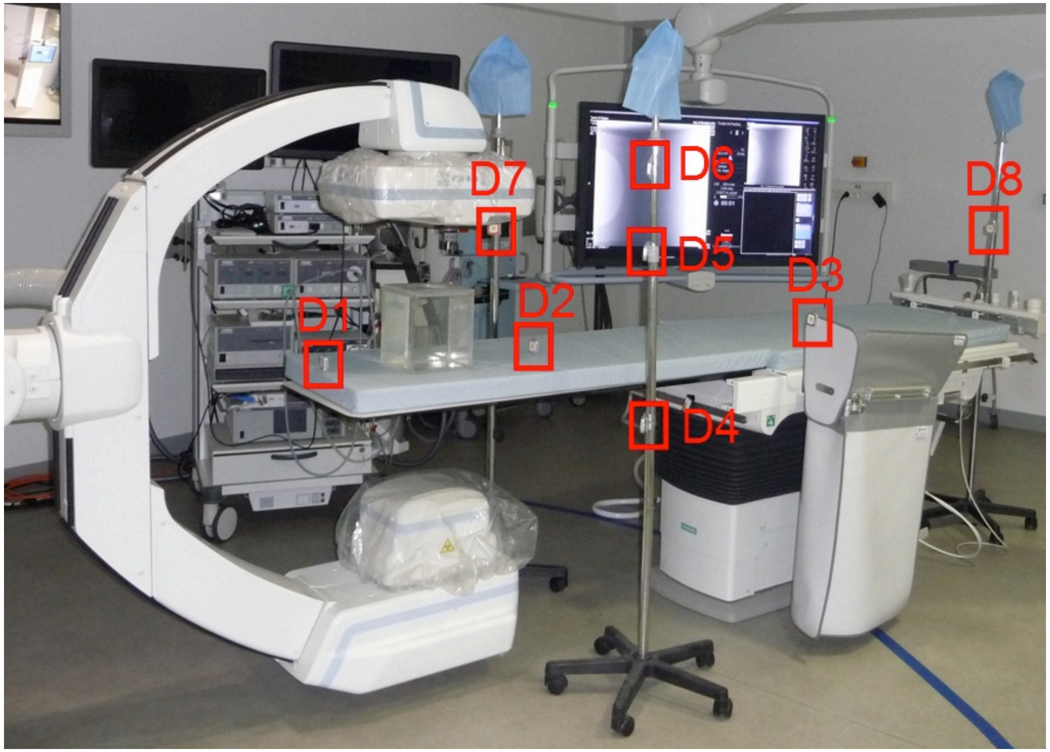


N. Loy Rodas et al., IEEE TBME, 2016

Validation Methodology

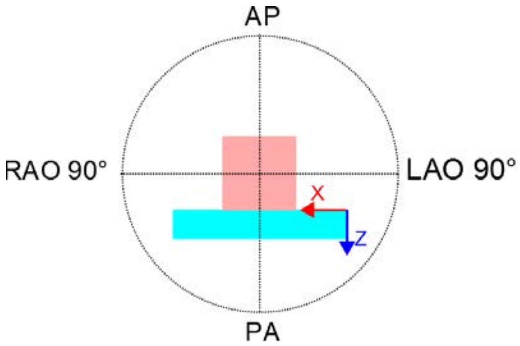
Experiments in a real operating room using:

- Artis Zeego X-Ray robotized imaging device
- 20x20x24 cm slab phantom filled with water
- 8 Raysafe i2 dosimeters (2 for calibration)



RaySafe dosimeters placement

Validation Methodology



4 beam projections per radiograph

Experiments in a real operating room using:

- Artis Zeego X-Ray robotized imaging device
- 20x20x24 cm slab phantom filled with water
- 8 Raysafe i2 dosimeters (2 for calibration)

Five fluoroscopy protocols w/ default params.

- 3 Digital Radiography (DR)
- 2 Digital Subtracted Angiography (DSA)

Simulation runs:

- 5 x 500M particles per protocol ; dose values normalized per particle and averaged over all runs.

30% average error over all test dosimeters, all radiograph protocols and C-arm rotations

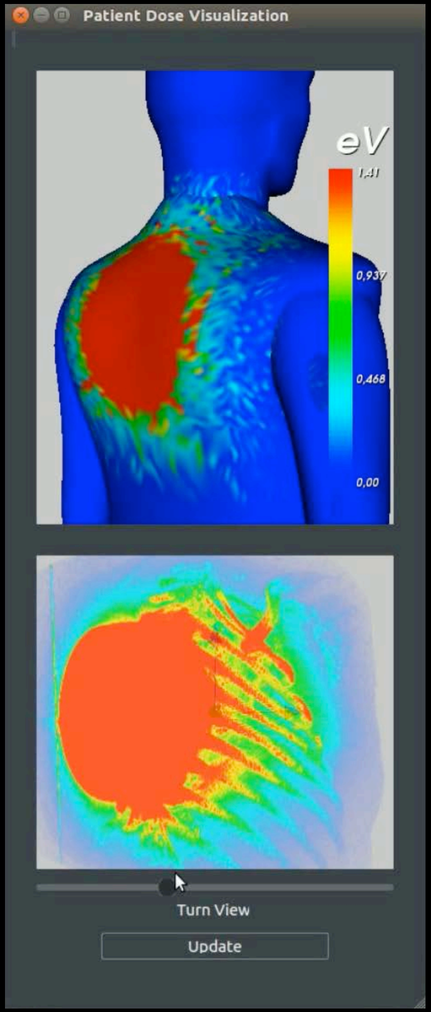
N. Loy Rodas, N. Padoy. **Seeing Is Believing: Increasing Intraoperative Awareness to Scattered Radiation in Interventional Procedures by Combining Augmented Reality, Monte Carlo Simulations and Wireless Dosimeters**. International Journal of Computer Assisted Radiology and Surgery (IJCARS), 2015

X-ray Safety Monitoring

3D Propagation:

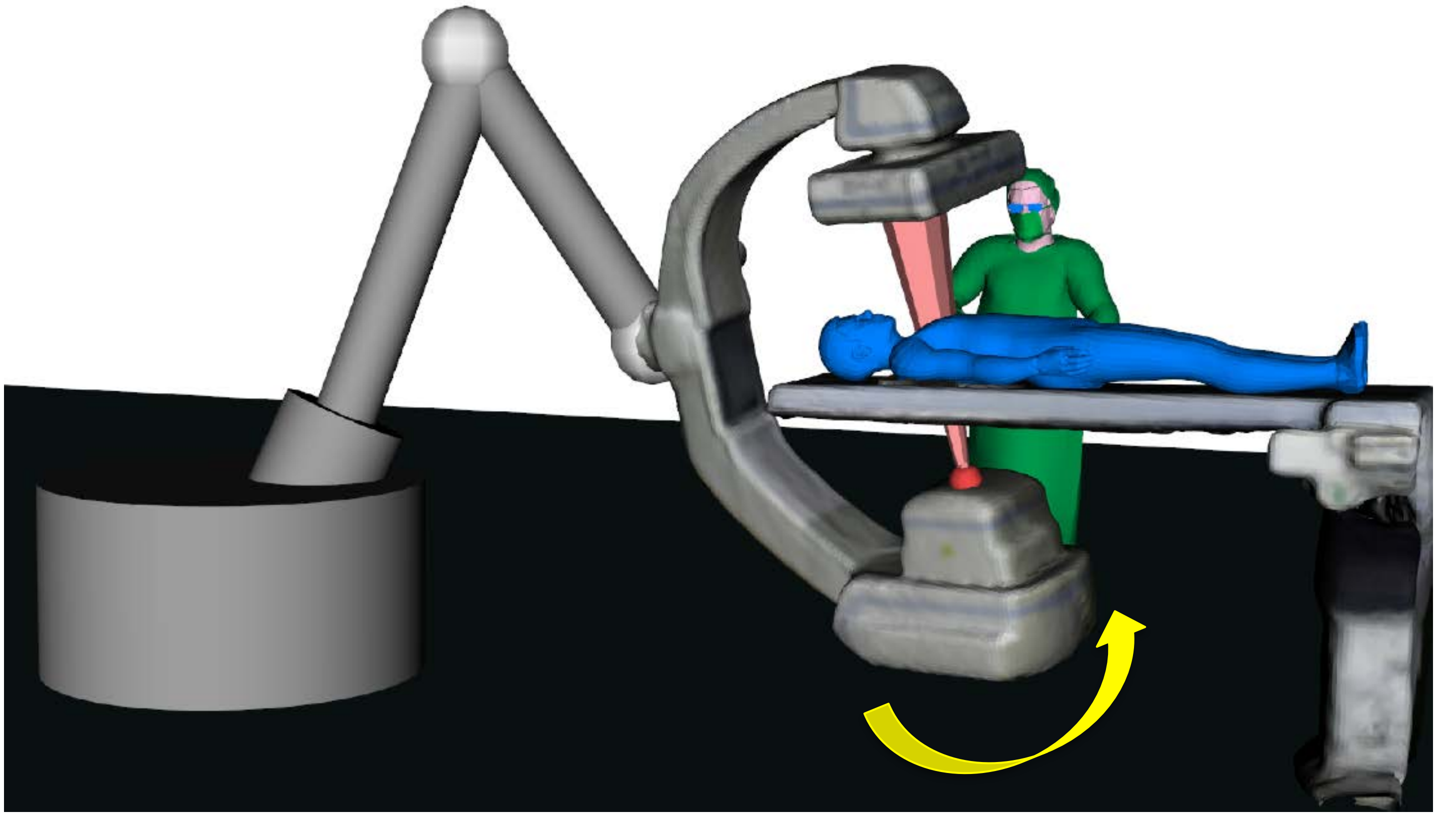
Body Parts:

Patient:



N. Loy Rodas, F. Barrera, N. Padoy. **See It With Your Own Eyes: Marker-less Mobile Augmented Reality for Radiation Awareness in the Hybrid Room**. IEEE Transactions on Biomedical Engineering, 2016

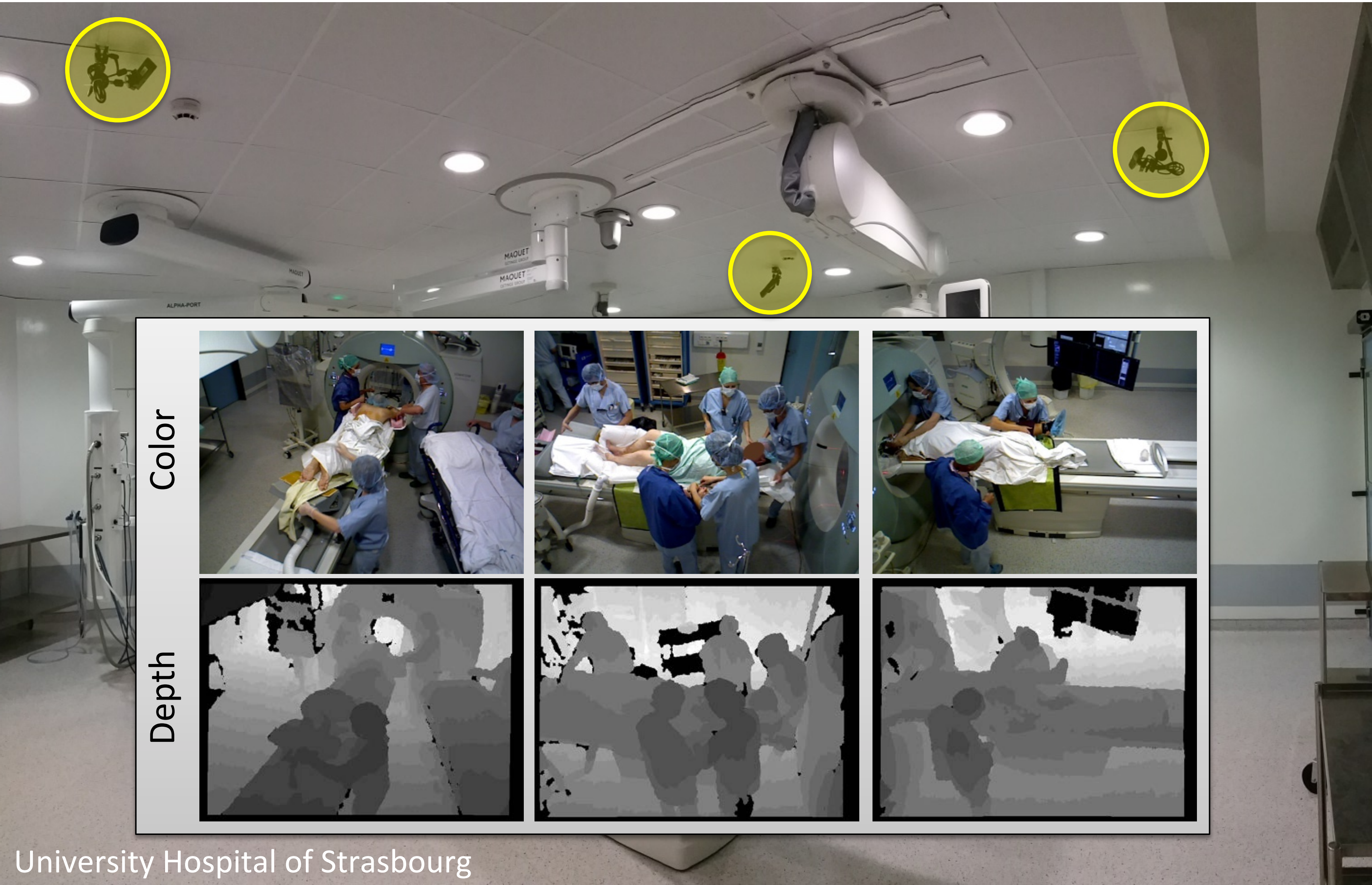
Automatic C-arm Pose Optimization



(Patent pending)

N. Loy Rodas, J. Bert, D. Visvikis, M. de Mathelin, N. Padoy, **Pose optimization of a C-arm imaging device to reduce intraoperative radiation exposure of staff and patient during interventional procedures**, ICRA 2017

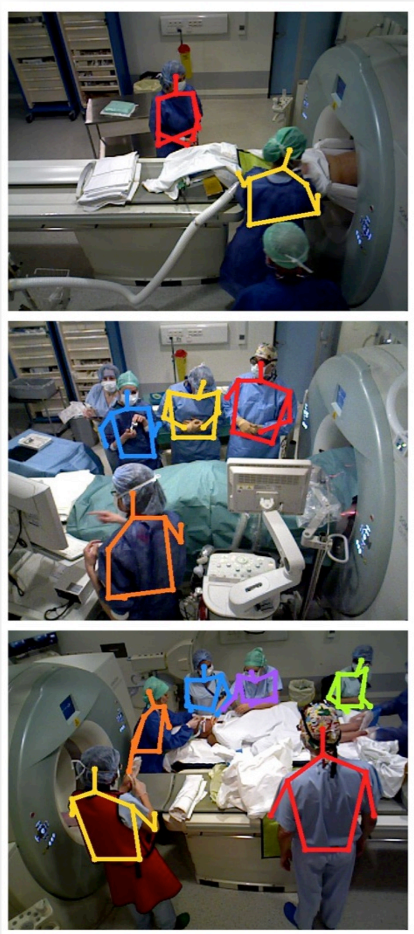
Multi-RGBD Camera System



University Hospital of Strasbourg

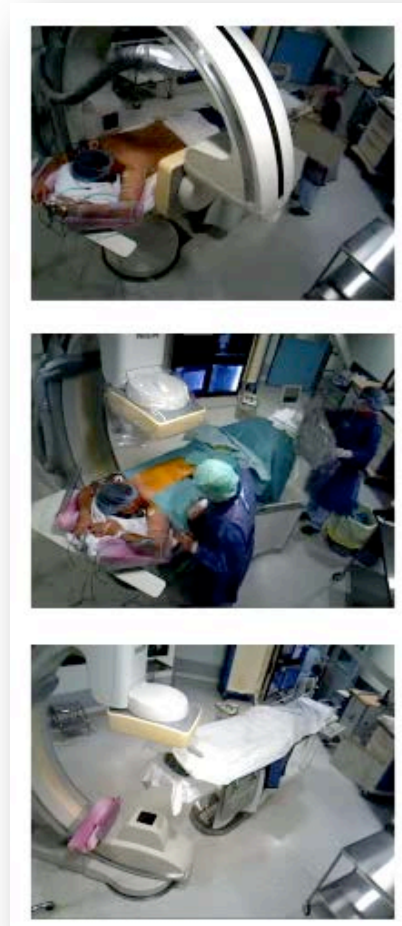
Beyond Visualization

Pose estimation

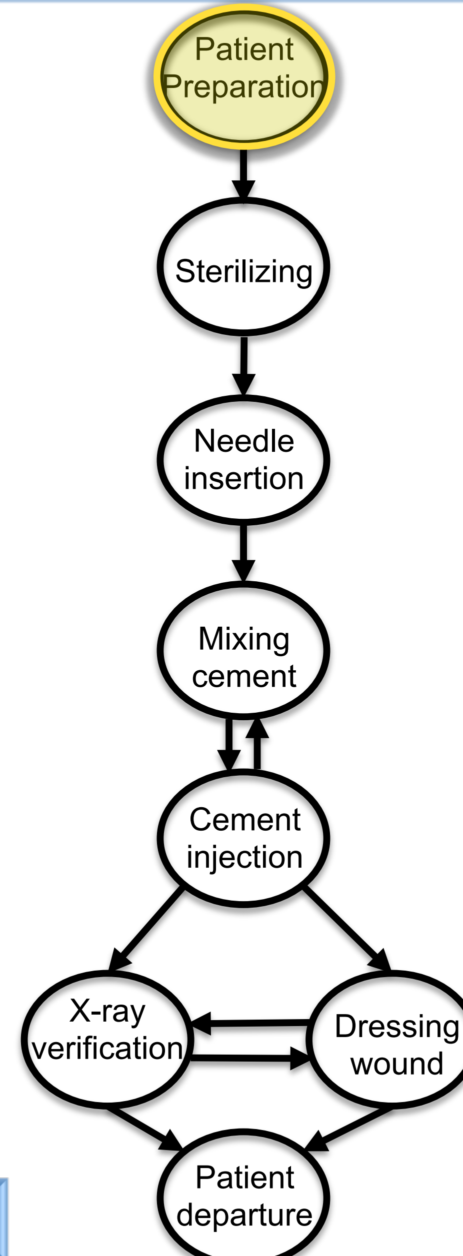


[Kadkhodamohammadi MedIA 2017]

Activity Recognition

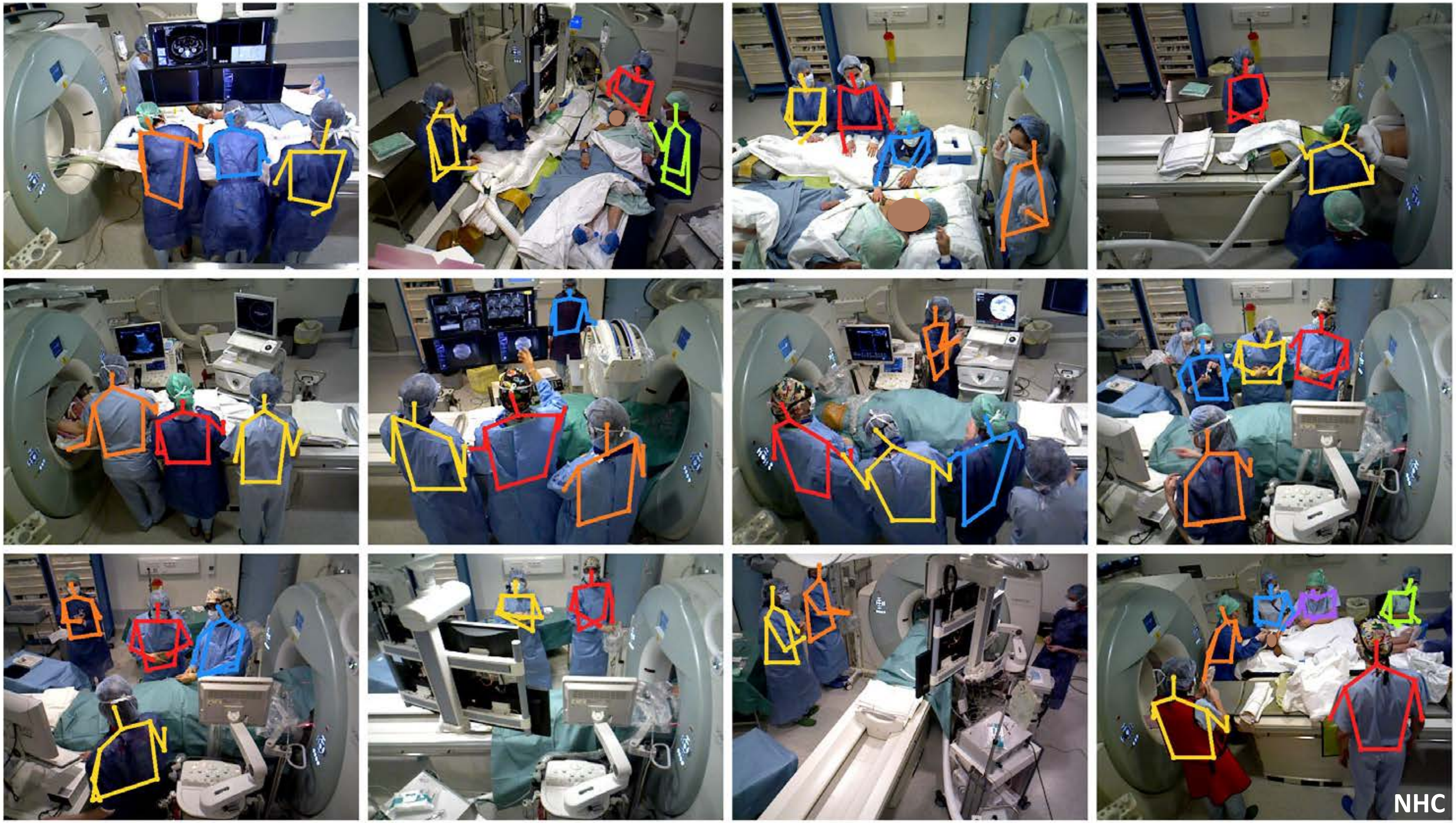


[Twinanda M2CAI 2016]



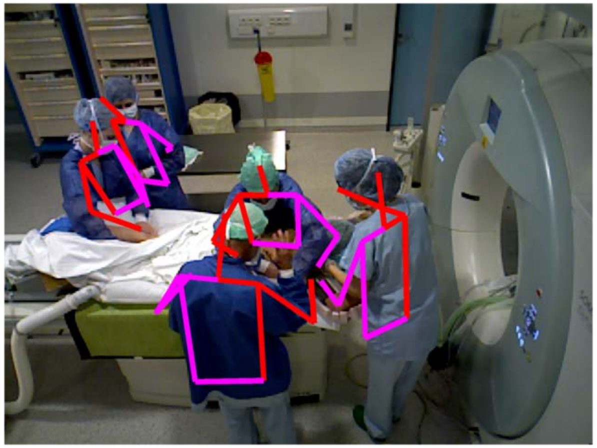
- Compute objective statistics about radiation exposure?

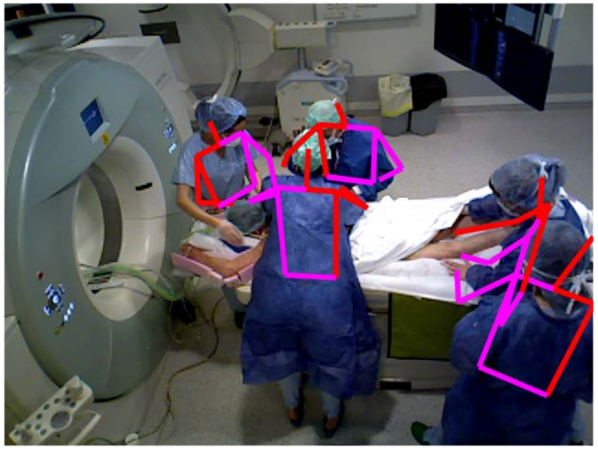
Clinician Pose Estimation

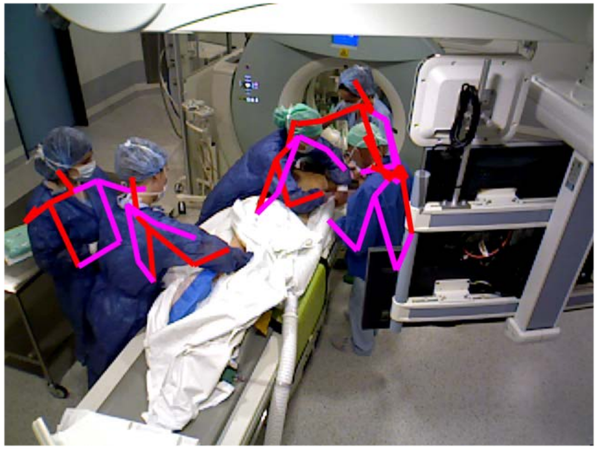


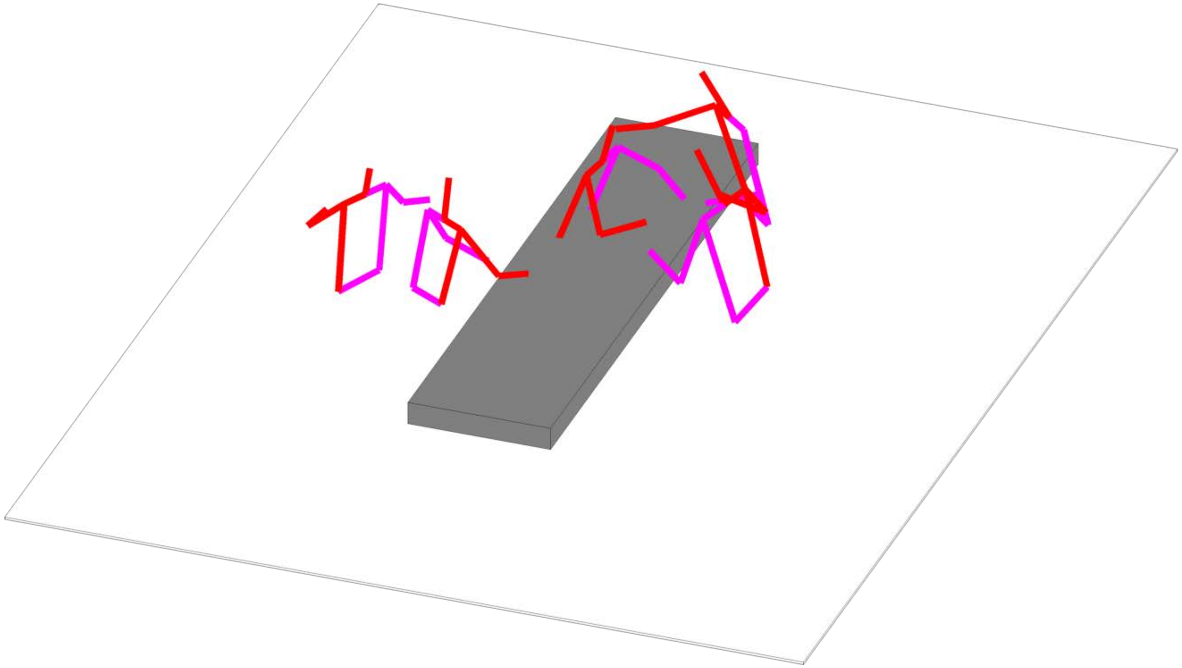
A. Kadkhodamohammadi, A. Gangi, M. de Mathelin, N. Padoy. **Articulated Clinician Detection Using 3D Pictorial Structures on RGB-D Data.** *Elsevier Medical Image Analysis*, 2017

Multi-view 3D Clinician Detection



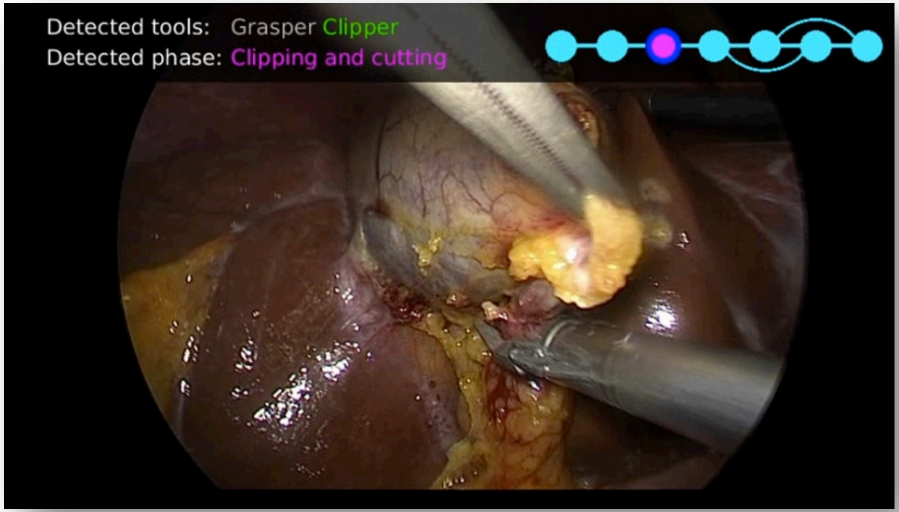






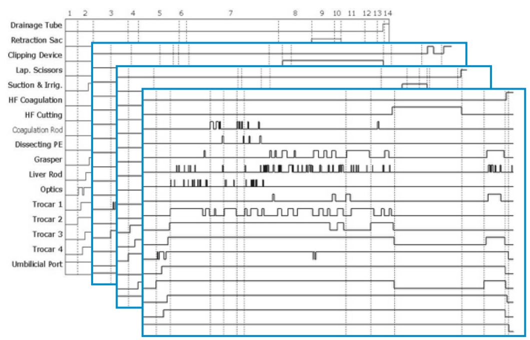
A. Kadkhodamohammadi, N. Padoy, **A generalizable approach for multi-view 3D human pose regression**, arXiv:1804.10462, 2018

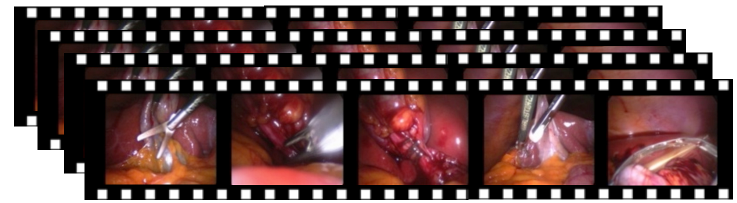
Endoscopic Surgery Monitoring

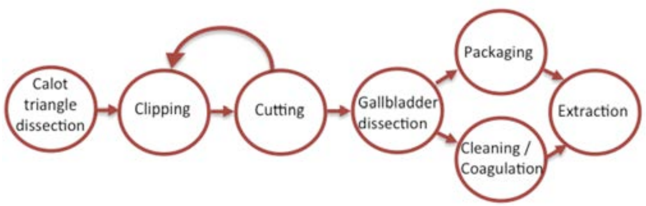


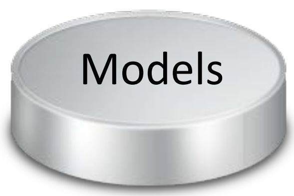
Clinical partners: IHU Strasbourg & IRCAD & Nouvel Hôpital Civil (Department of Digestive Surgery)

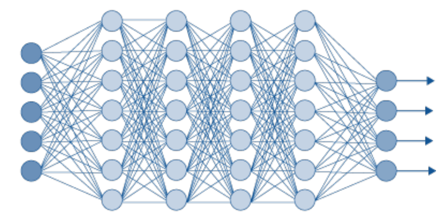
What can we learn from endo data?









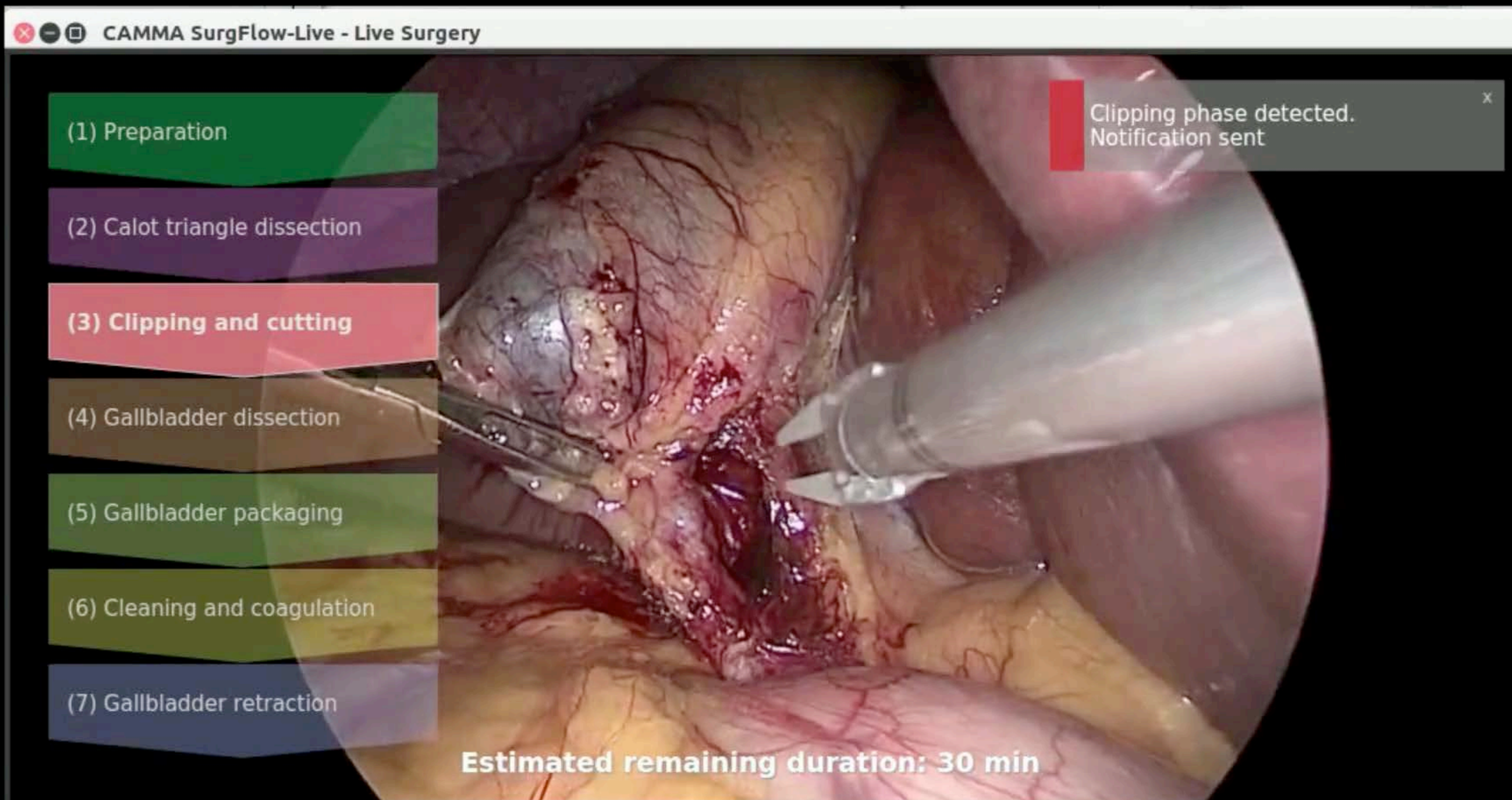


Current surgery

Recognition & Prediction Methods

- **Live feed about OR status**
- **Automated checkpoints**
- **Anomaly detection**
- **Visualization of contextual data**
- **Robotic assistance**
- **…**

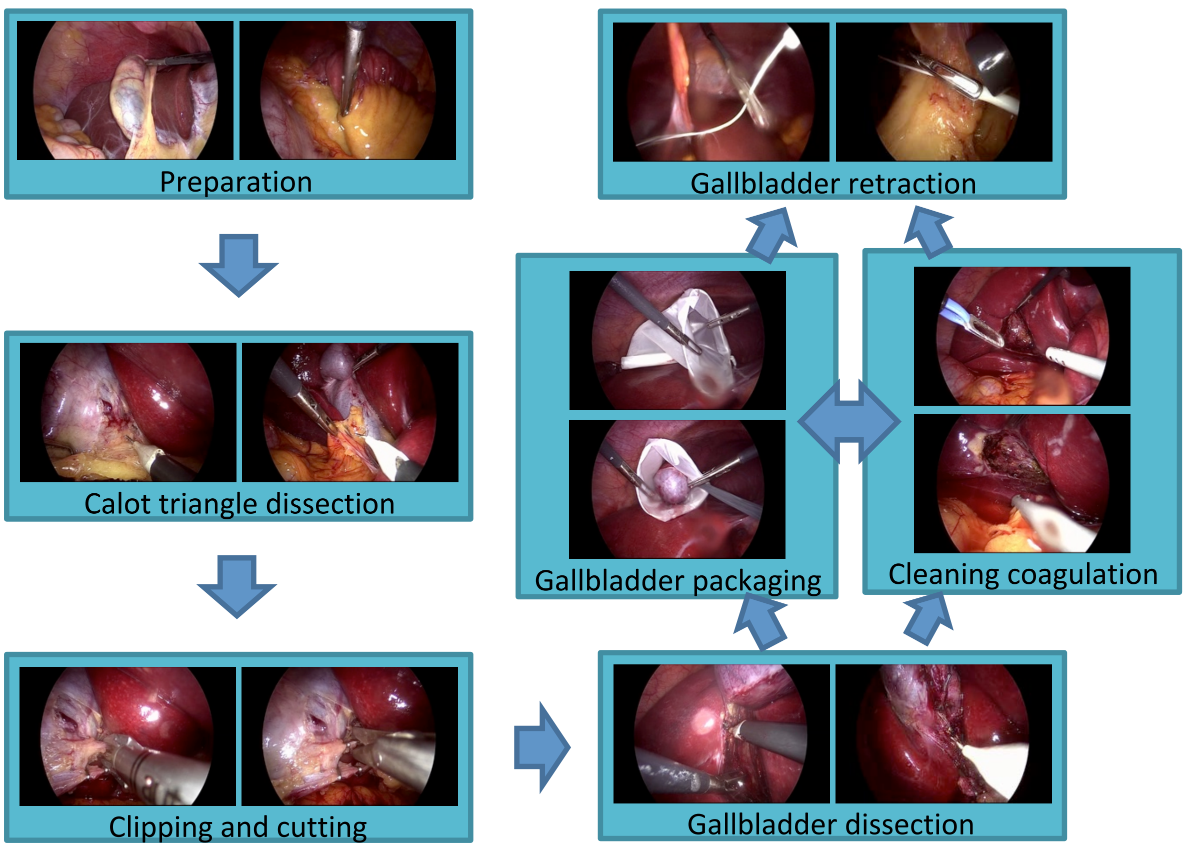
Automated Analysis of Endoscopic Videos

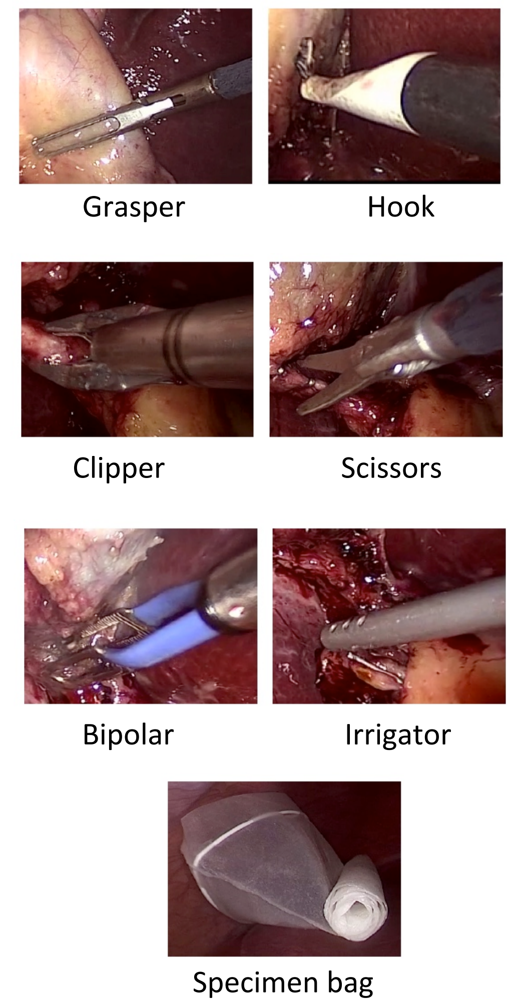


A.P. Twinanda, S. Shehata, D. Mutter, J. Marescaux, M. de Mathelin, N. Padoy. **EndoNet: A Deep Architecture for Recognition Tasks on Endoscopic Videos.** IEEE Trans. on Medical Imaging, 2017
I. Aksamentov, A.P. Twinanda, D. Mutter, J. Marescaux, N. Padoy. **Deep Neural Networks Predict Remaining Surgery Duration from Cholecystectomy Videos**. MICCAI (Oral), 2017

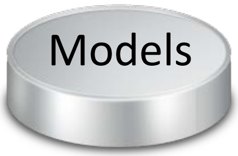
Data & Annotations

- Cholec120
- Videos: 120 endoscopic cholecystectomy procedures
- Annotations: workflow phases and binary tool presence





Modeling



- Current phase prediction:

$$f(\mathbb{O}_1 \dots \mathbb{O}_t) \rightarrow p \in \{1, \dots, 7\}$$

- Tool presence prediction:

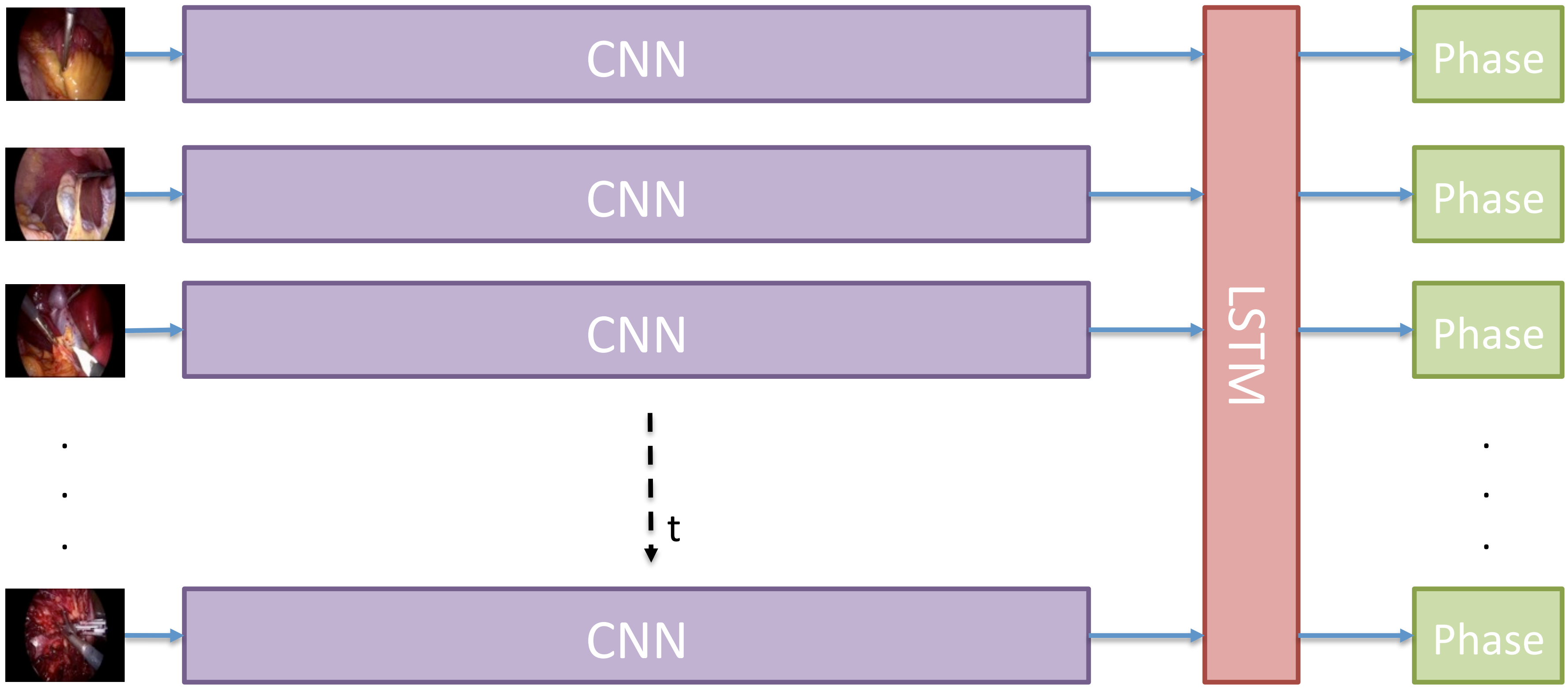
$$f(\mathbb{O}_1 \dots \mathbb{O}_t) \rightarrow i \in \{0, 1\}^7$$

- Remaining duration prediction:

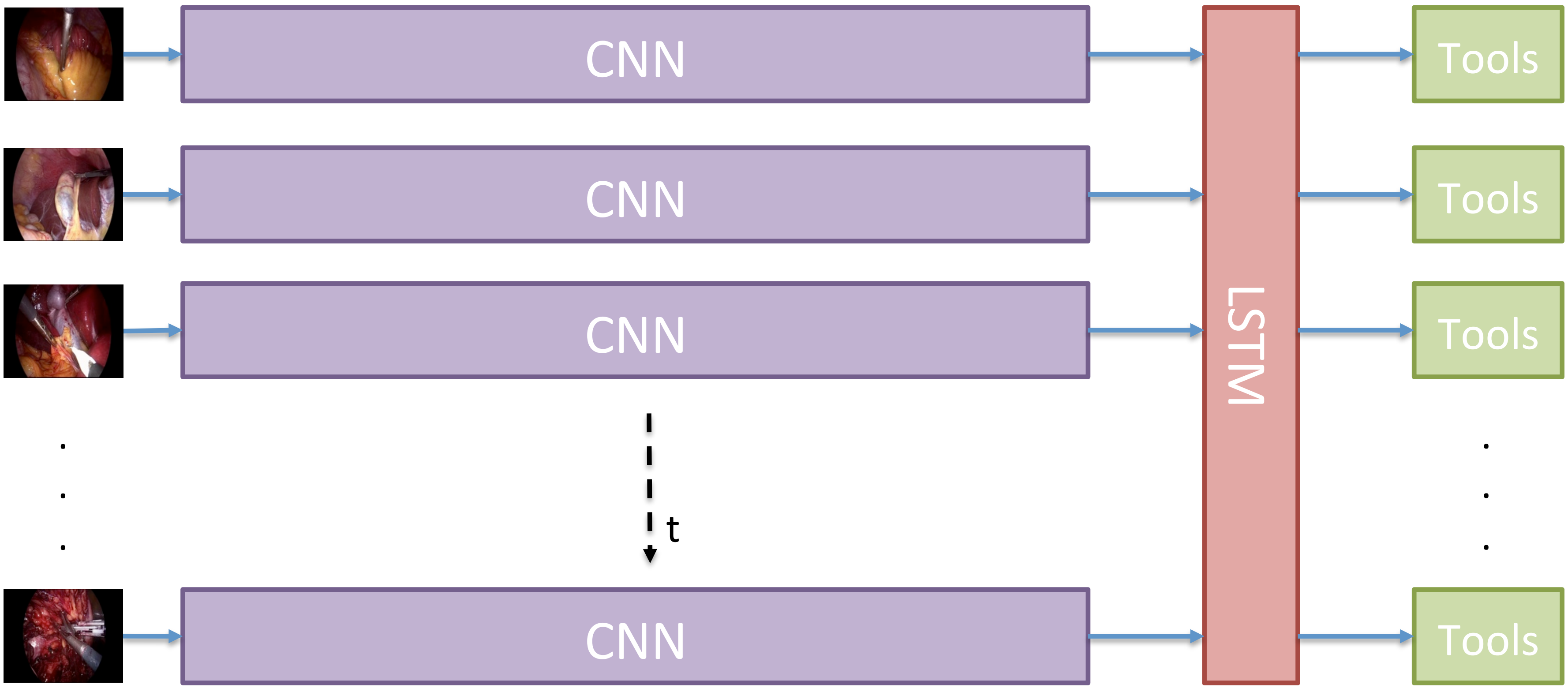
$$f(\mathbb{O}_1 \dots \mathbb{O}_t) \rightarrow r \in \mathbb{N}$$

Learn f from 10^2, 10^3, … , 10^6, … surgeries with minimal supervision

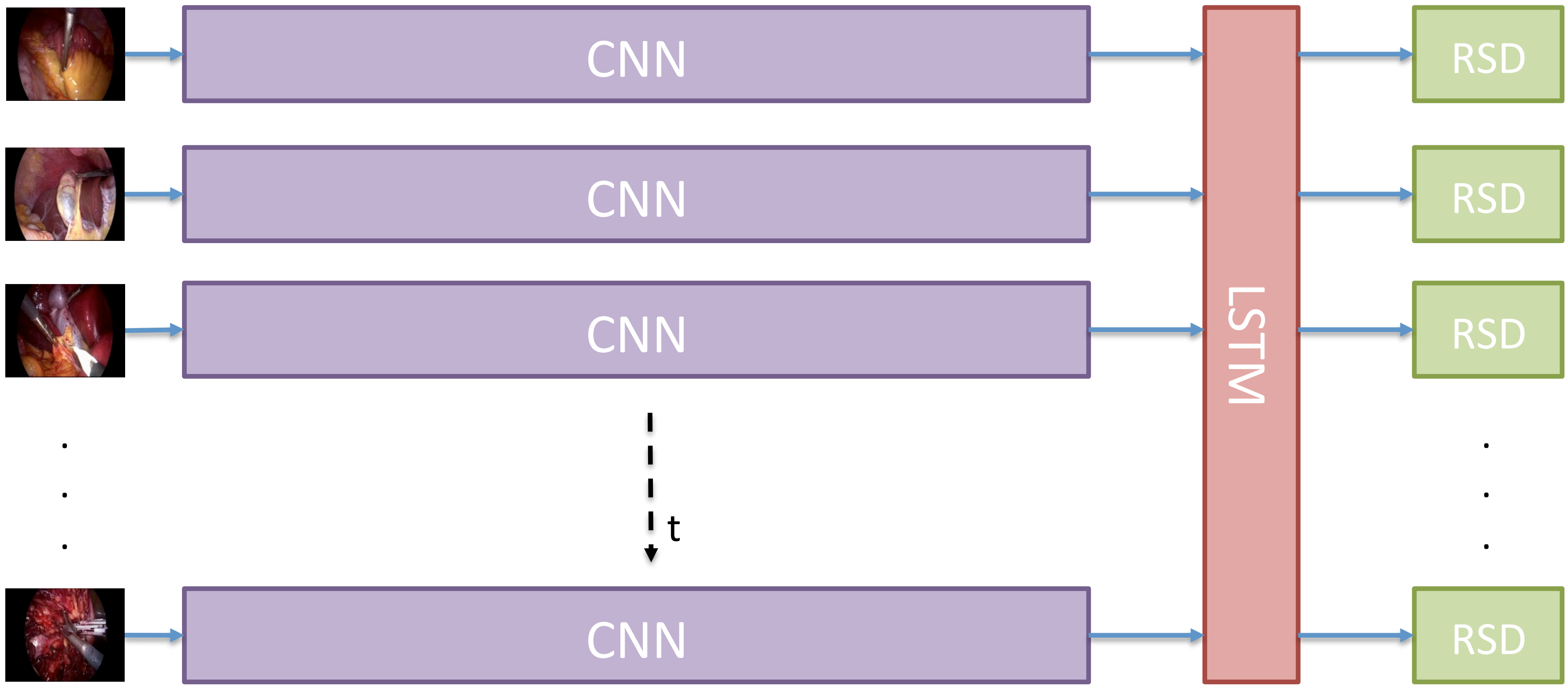
Deep Learning Pipeline



Deep Learning Pipeline

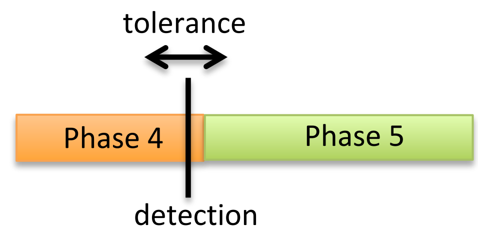


Deep Learning Pipeline



Phase Recognition Results

- Accuracy (online): 89%



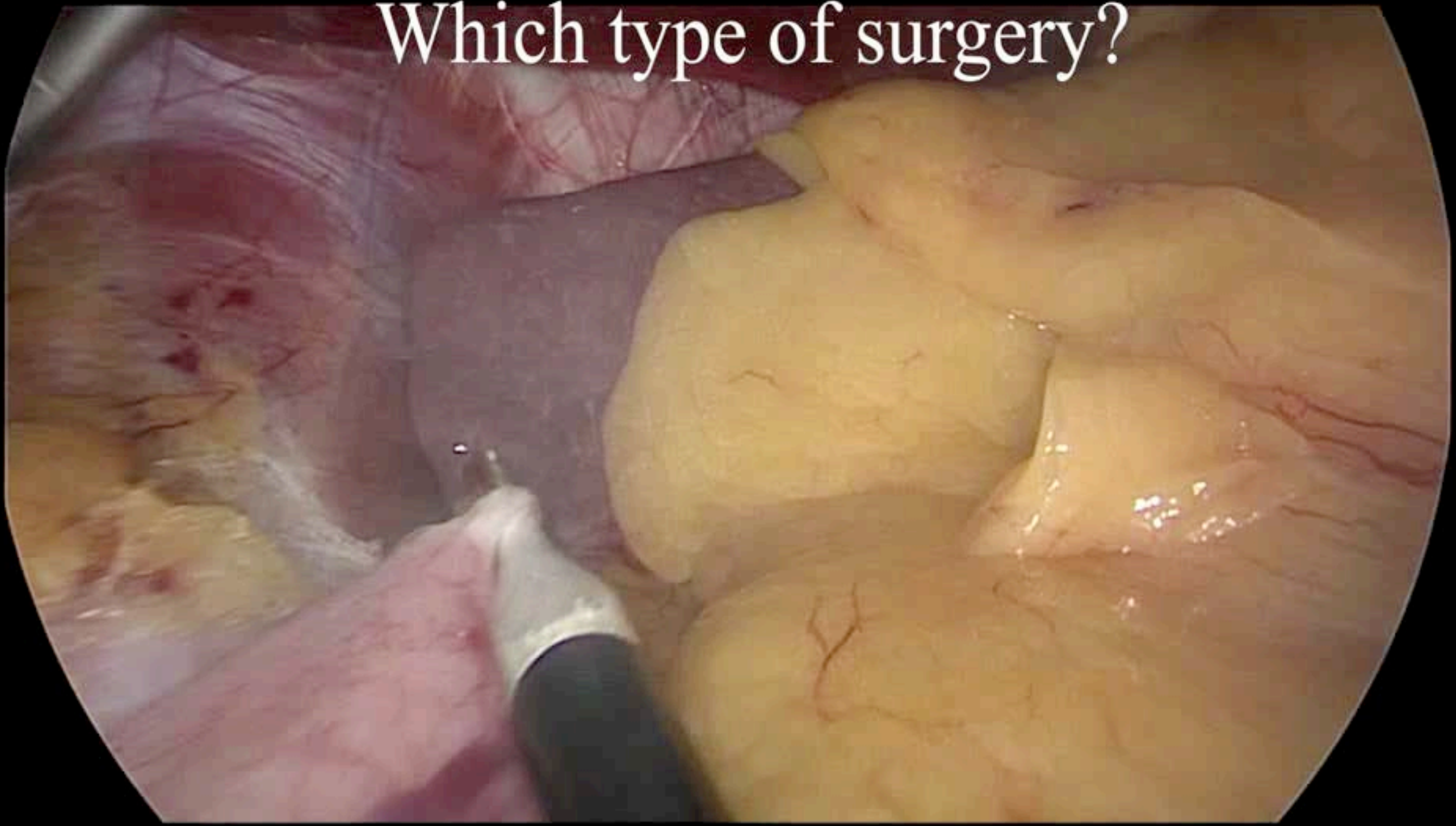
Tolerance (s)	Surgical Phase Id						
	1	**2**	**3**	**4**	**5**	**6**	**7**
< 30	40	36	35	31	39	25	30
30-59	0	2	2	2	1	3	1
60-89	0	1	1	2	0	7	7
90-119	0	1	2	5	0	0	2
120	0	0	0	0	0	0	0
TOTAL	40	40	40	40	40	35	40

- All phases are detected in a bounded tolerance of 2 minutes
- Most of the phases are detected less than 30 seconds early/late

Ongoing Research Questions

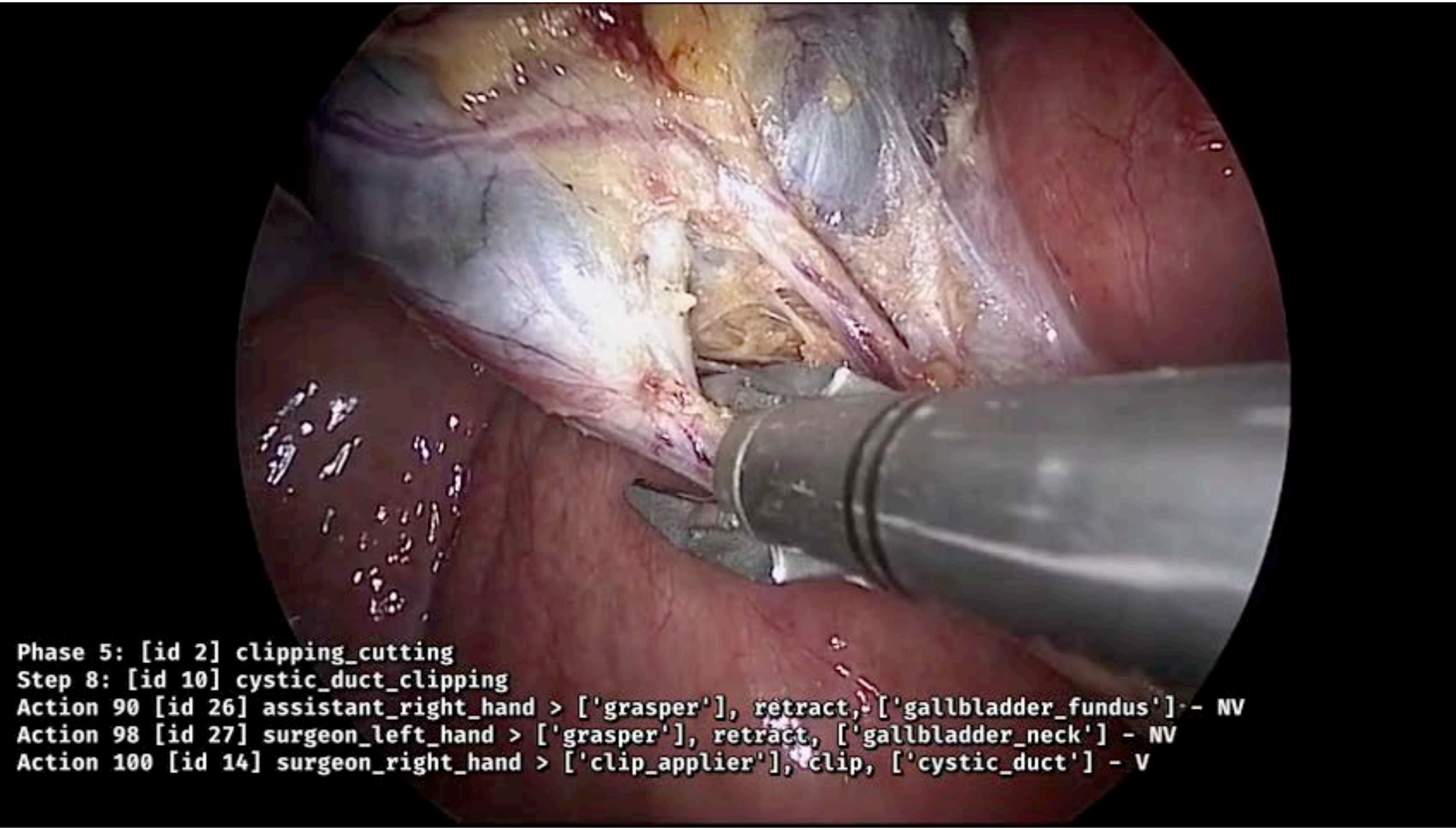
Early Surgery Type Recognition

$$\underset{s}{\operatorname{argmax}} P(\text{surgery\_type} = s | I_0 \ldots I_t) \quad t < 15\text{mn}$$



A.P. Twinanda, J. Marescaux, M. de Mathelin, N. Padoy, **Classification approach for automatic laparoscopic video database organization**, IJCARS 2015
S. Kannan, G. Yengera, D. Mutter, J. Marescaux, N. Padoy, **Future-State Predicting LSTM for Early Surgery Type Recognition**, arXiv 2018

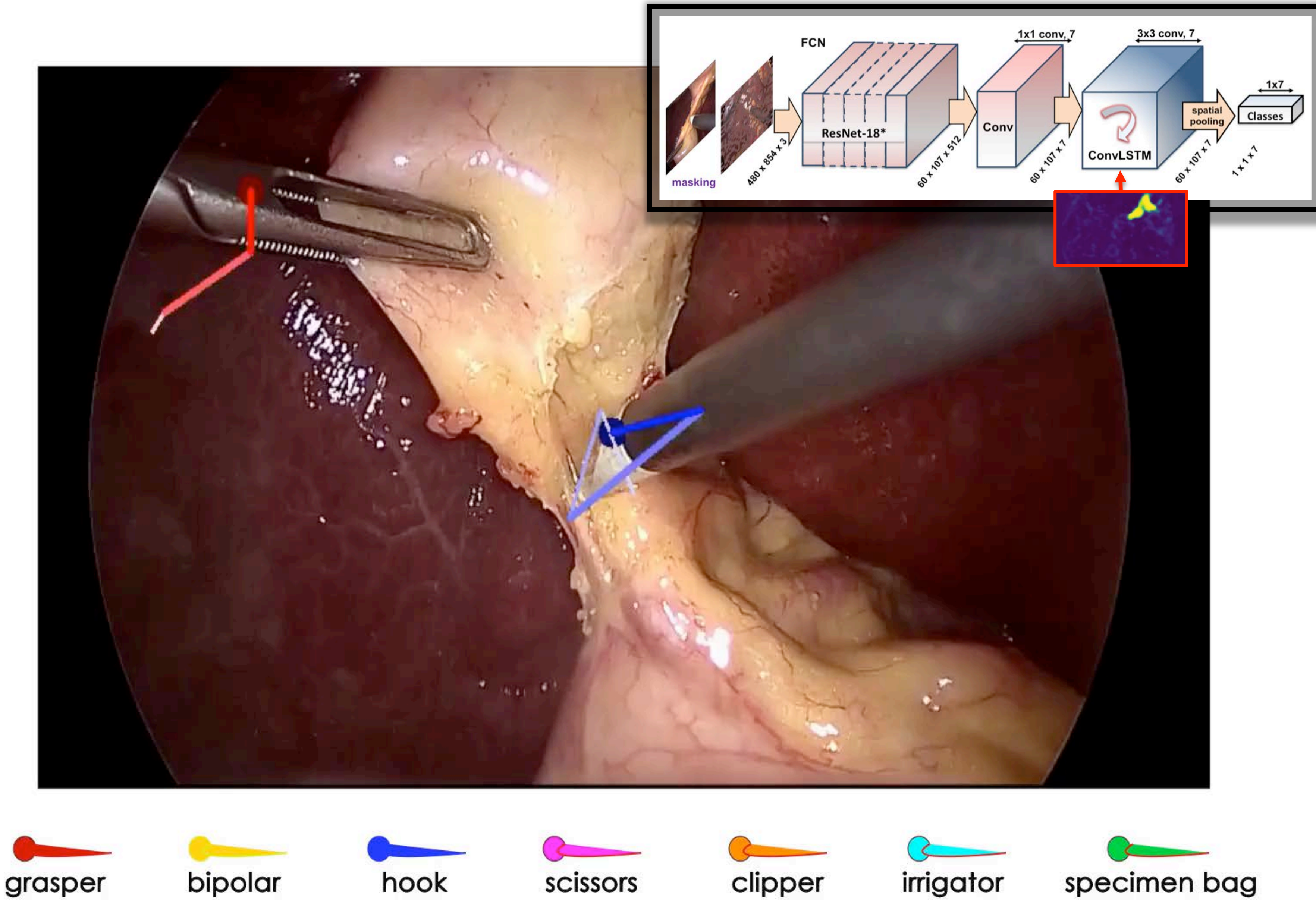
Language of Surgery Recognition



T. Yu, D. Mutter, J. Marescaux, N. Padoy, Learning from a tiny dataset of manual annotations: a teacher/student approach for surgical phase recognition, IPCAI 2019

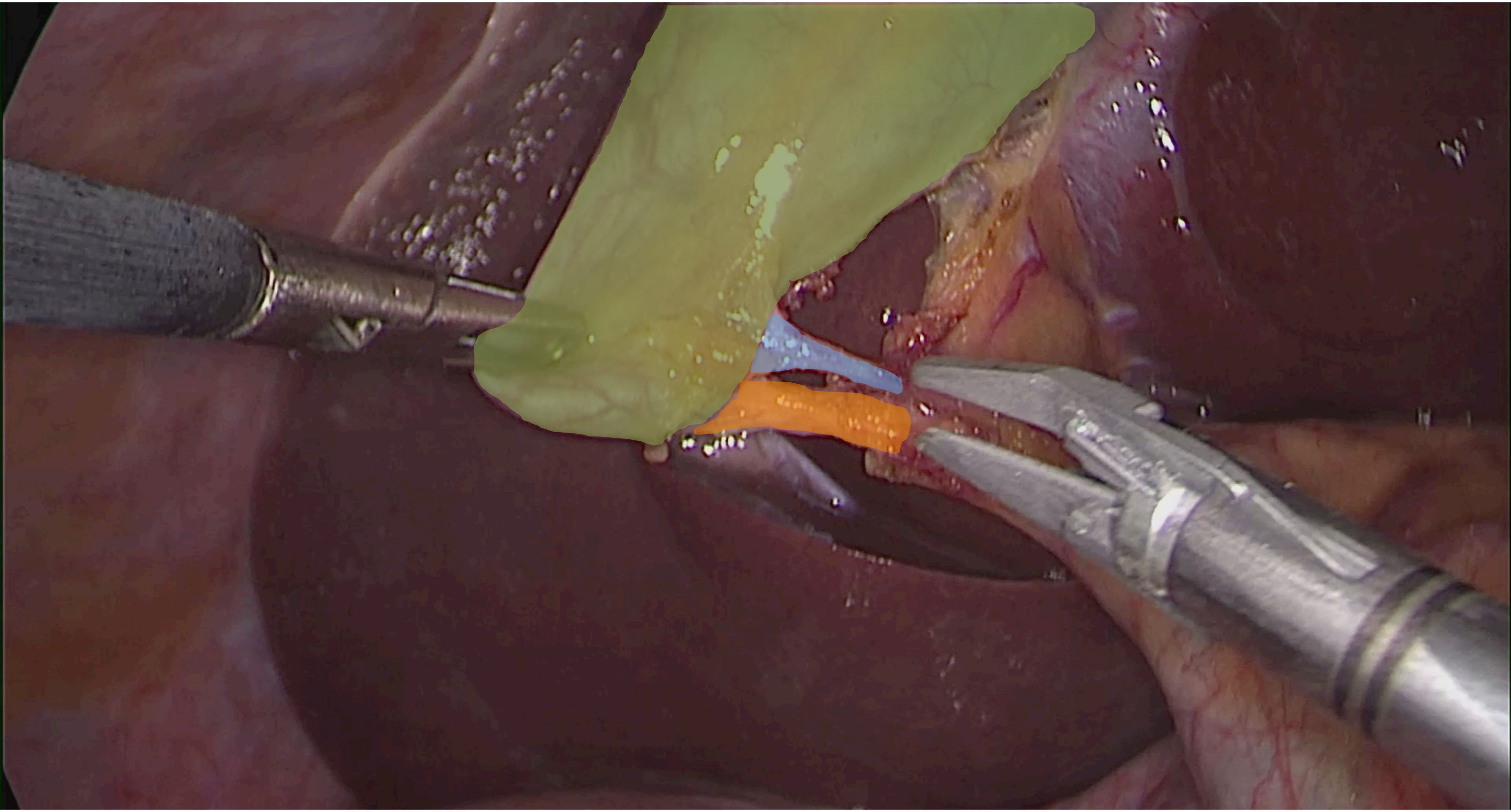
CONDOR Connected Optimized Network & Data in Operating Rooms

Weakly-Supervised Localization



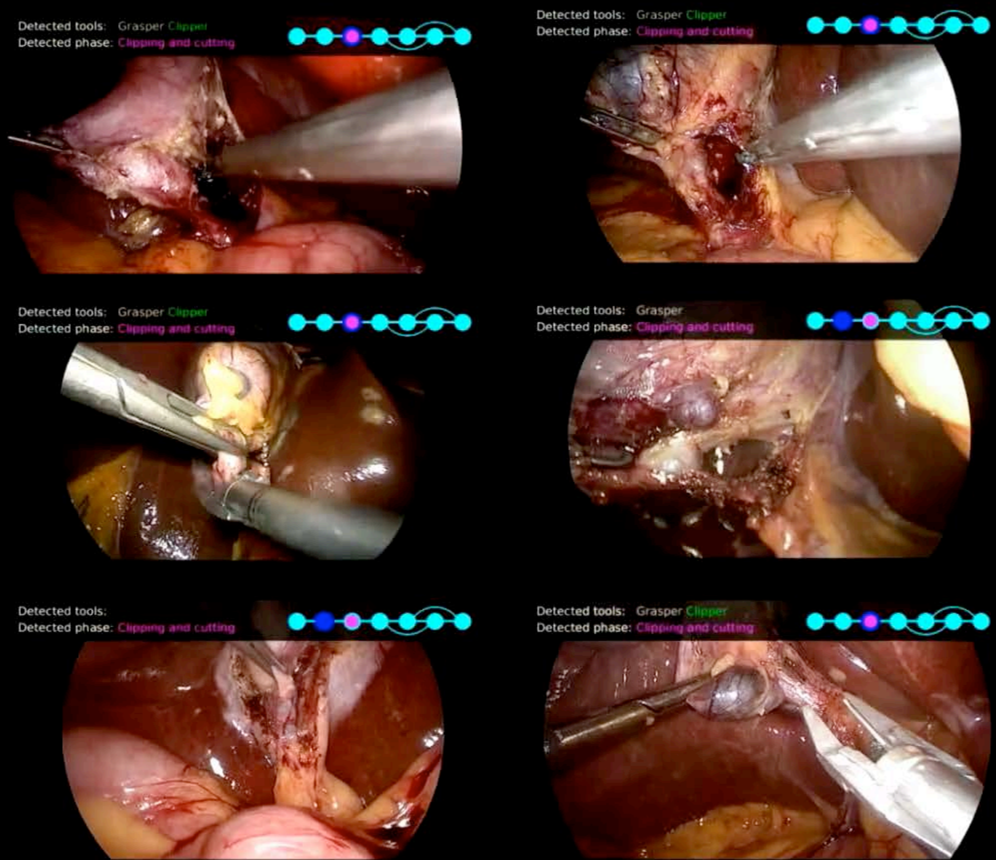
C.I. Nwoye, D. Mutter, J. Marescaux, N. Padoy, Weakly Supervised Convolutional LSTM Approach for Tool Tracking in Laparoscopic Videos, IPCAI/IJCARS 2019

Anatomy Detection



Pietro Mascagni et al., 2019

Automated OR Assistant



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A.P. Twinanda, S. Shehata, D. Mutter, J. Marescaux, M. de Mathelin, N. Padoy. **EndoNet: A Deep Architecture for Recognition Tasks on Endoscopic Videos.** IEEE Transactions on Medical Imaging, 2016

Conclusion

- Operating Room is a new application domain for AI & Vision
- How to scale up
  - To more types of surgeries
  - To more complex workflows
  - To more clinical applications
  - With privacy-preserving data
  - With less manual annotation and human supervision

- How to demonstrate clinical benefits?

Thanks for your attention!

Research Group CAMMA
ICube, University of Strasbourg

http://camma.u-strasbg.fr

MVOR and Cholec80 datasets:
http://camma.u-strasbg.fr/datasets

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FLI ExpoMRI
FLI ROBOPTX
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