

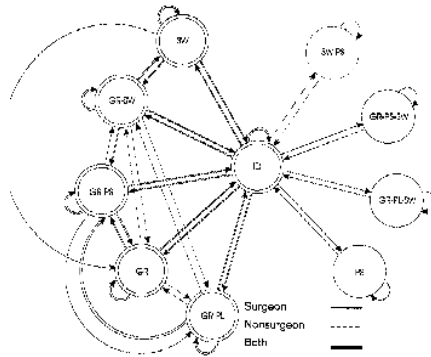
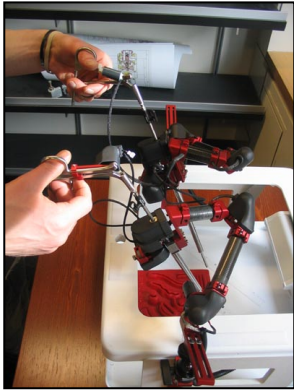
Spatio-temporal Registration of Multiple Gestures for Skills Analysis and Automation in Robotic Surgery

Nicolas Padoy

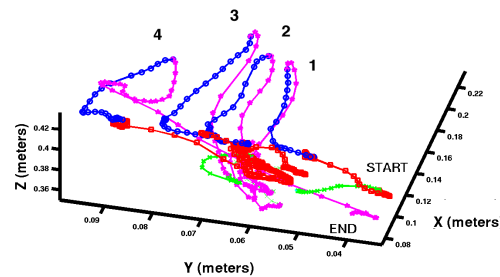
University of Strasbourg, France



Introduction



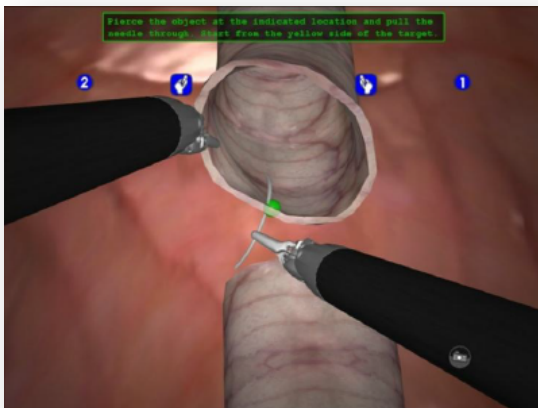
Rosen, Brown, Chang, Sinanan, Hannaford. **Generalized approach for modeling minimally invasive surgery as a stochastic process using a discrete markov model.** IEEE Transactions in Biomedical Engineering, 53(3):399–413, 2006.



Lin, Shafran, Yuh, Hager. **Towards automatic skill evaluation: Detection and segmentation of robot-assisted surgical motions.** Computer Aided Surgery, 11(5):220–230, 2006

- Few experiments using such techniques on real data
- Other applications can benefit from gesture modeling

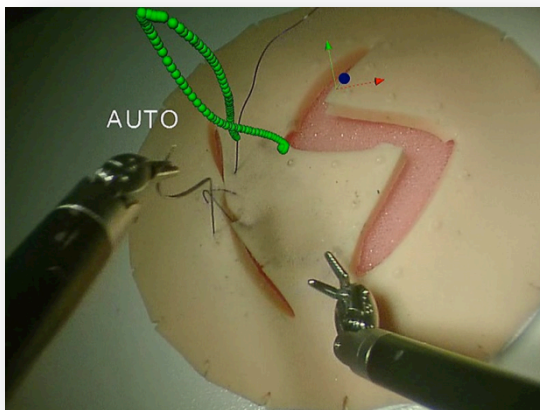
Motivation for Gesture Analysis (1)



Mimic da Vinci simulator

Skills analysis

- Trainee evaluation
- Automated feedback
- **Skills understanding**



Robotic automation

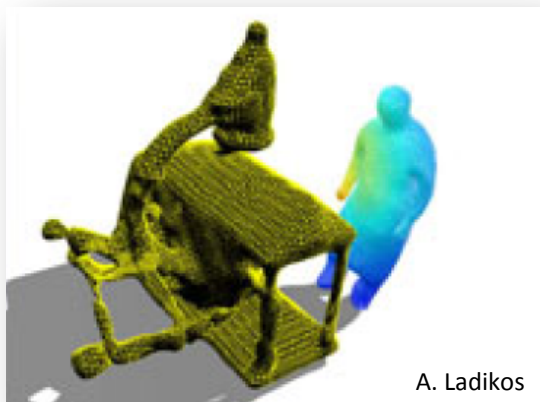
- Motion replay
- Virtual fixtures
- **Shared control**

Motivation for Gesture Analysis (2)



Context recognition

- Context-aware UI
- OR synchronization
- Reports

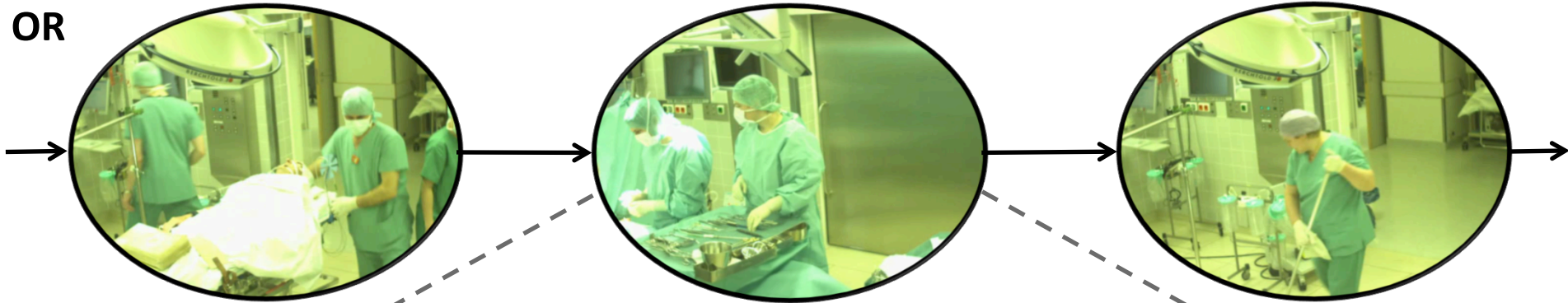


Safety monitoring

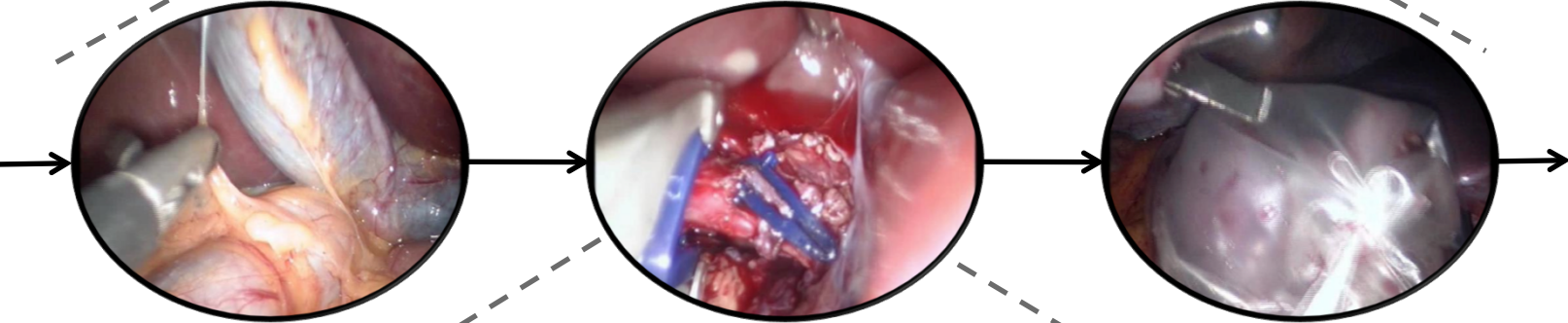
- Tool-tissue interactions (patient)
- Ergonomy analysis (staff)
- Radiation monitoring (staff)

Need for a language of surgical activities...

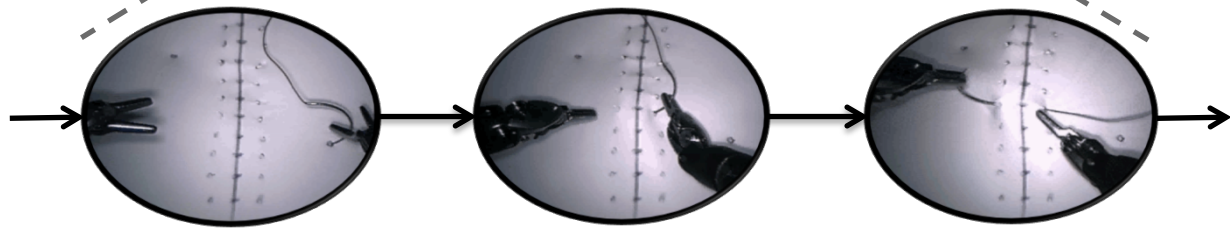
OR



STEP



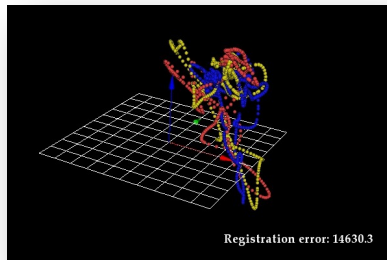
GESTURE



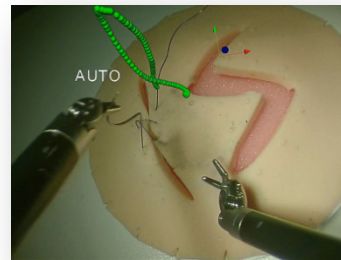
...and for an OR perception and recognition system

Outline

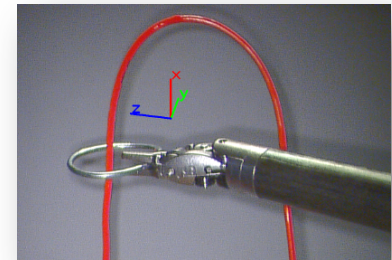
Gesture Modeling and Human-machine collaboration using the da Vinci robot



Surgical gesture modeling
(MICCAI'2011)

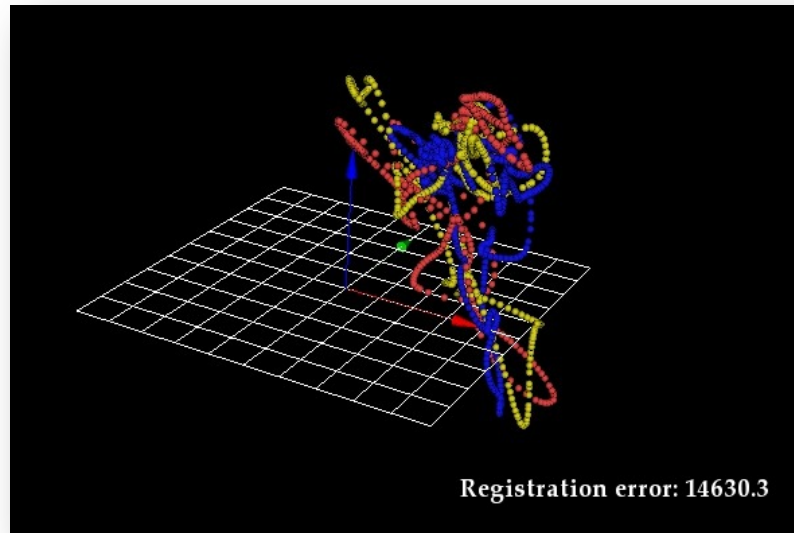


Shared Control
(ICRA'2011)

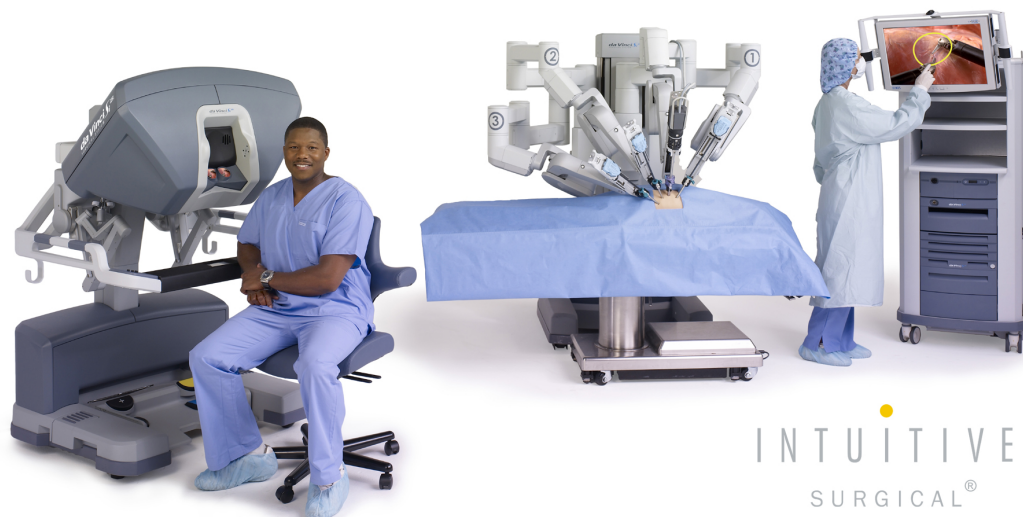


Active fixtures
(RLIHT'2012)

Gesture Modeling



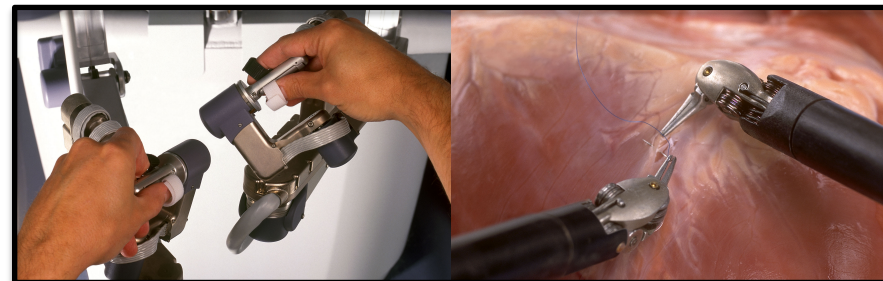
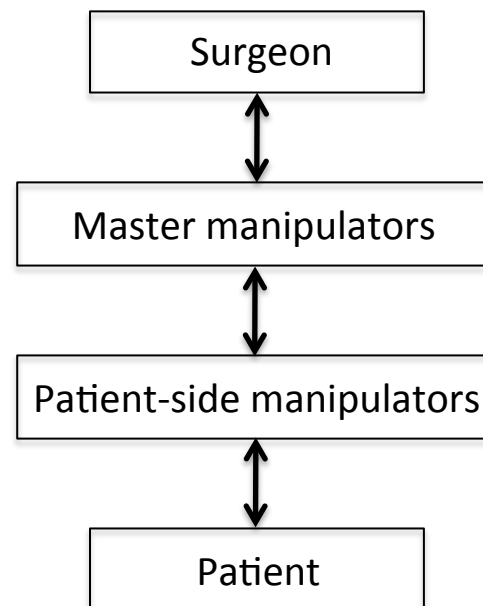
The da Vinci Robot



INTUITIVE
SURGICAL®

Features

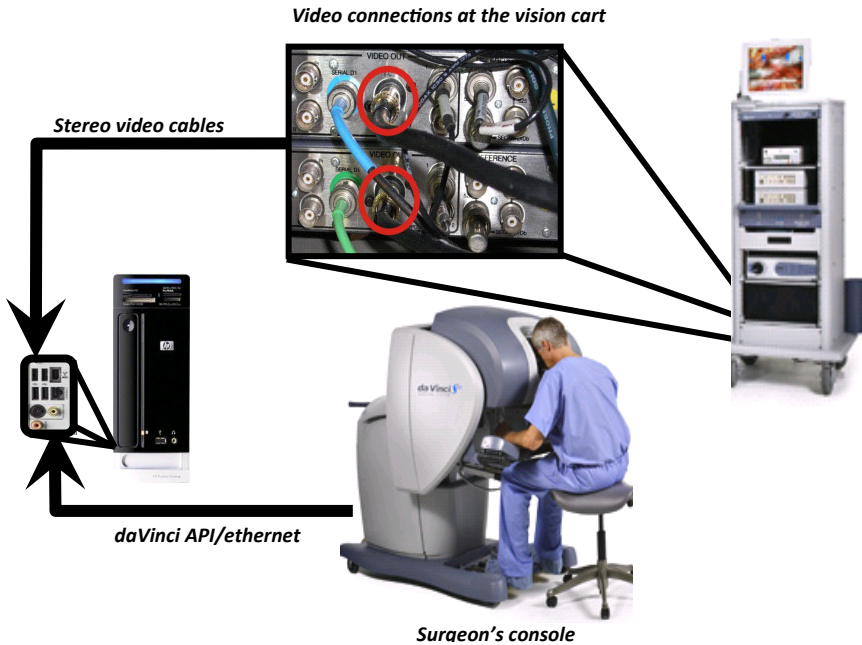
- 4 robotic arms
- HD stereo view
- 7 DOFs instruments
- Motion scaling
- Tremor filtering



Why is Robotic Surgery Well Suited?

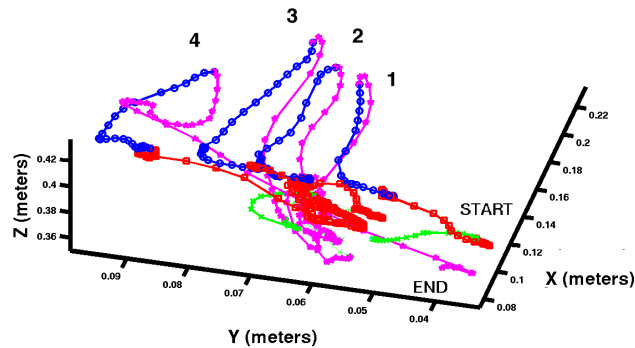


Language of Surgery Project @ JHU

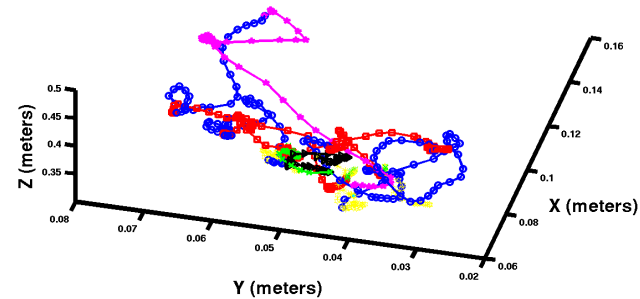


(Lin et al., MICCAI 2006)

- How can surgical skills be evaluated objectively ?

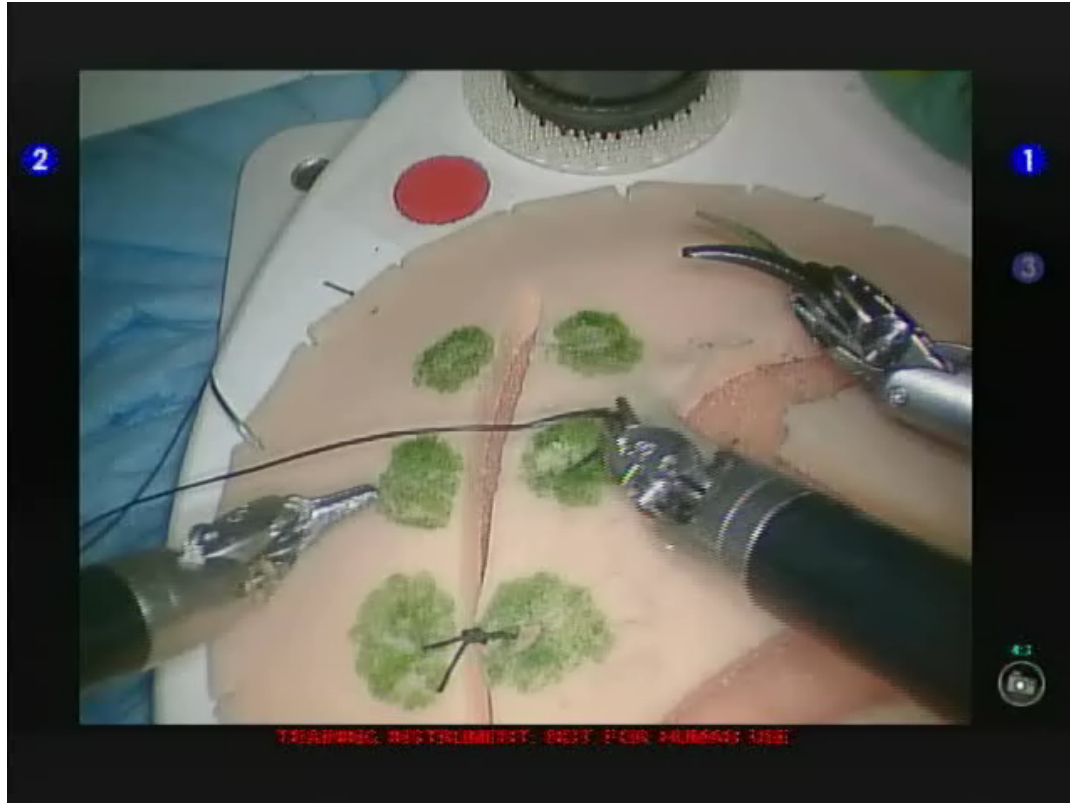


Expert Surgeon - trial 4



Intermediate Surgeon - trial 22

What about this dataset?



Kumar, Hager et al.

(speed x5)

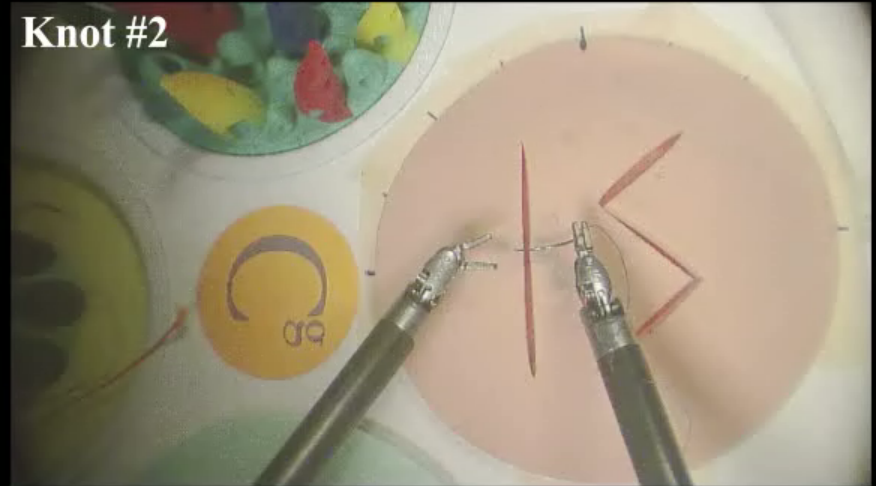
Longitudinal study of resident surgeons in several US hospitals over 4 training tasks

→ large data variability

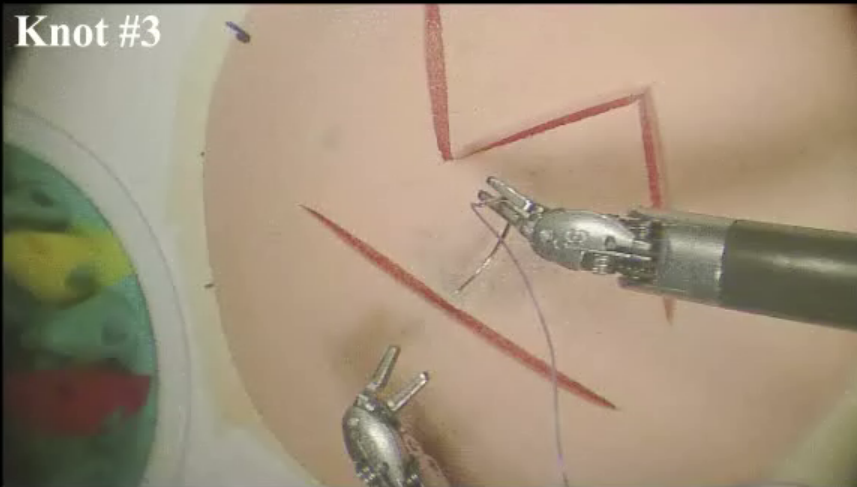
Knot #1



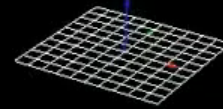
Knot #2



Knot #3



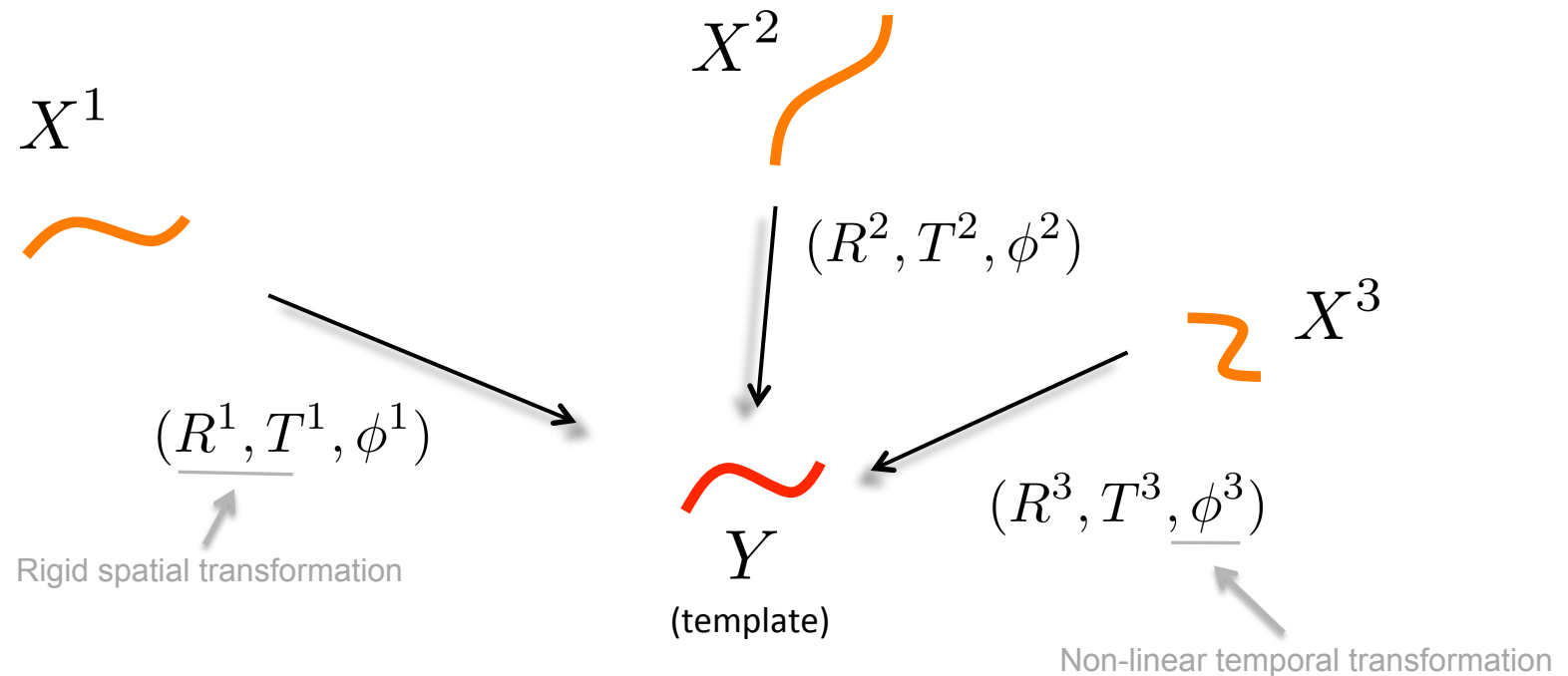
Left tool trajectories



Spatio-Temporal Registration Demo - Nicolas Padoy, CIRL, JHU

(raw data: 3 of 6 sequences)

Spatio-temporal Gesture Registration



- Spatial overlap
- Non-linear temporal variations
- Local and global spatial variations

Spatio-temporal Time Warping (STW)

→ Combine DTW with ICP to obtain better point correspondences (STW)

$$C_{warping}(\phi) = \sum_{t=1}^m \|X_{\phi_t^x} - Y_{\phi_t^y}\|^2 \quad (\text{DTW})$$

$$C_{rigid}(R, T) = \sum_{l=1}^p \|RU_{\psi^u(l)} + T - V_{\psi^v(l)}\|^2 \quad (\text{ICP})$$

$$C_{stw}(R, T, \phi) = \sum_{t=1}^m \|RX_{\phi_t^x} + T - Y_{\phi_t^y}\|^2 \quad (\text{STW})$$

→ Solve using coordinate descent

For multiple sequences, construct a template Y

$$C_{multi}(R^k, T^k, \phi^k) = \sum_{k=1}^K \sum_{t=1}^{m_k} \|R^k X_{\phi_t^k, x}^k + T^k - Y_{\phi_t^k, y}\|^2 \quad (\text{MDTW})$$

Algorithm 2. Template generation

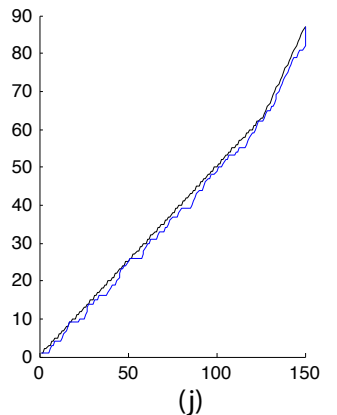
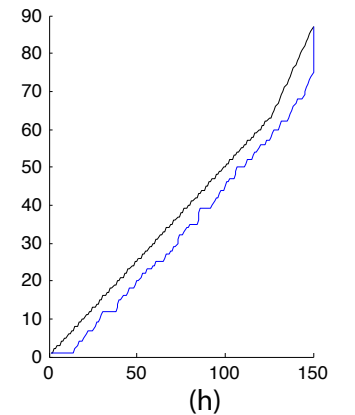
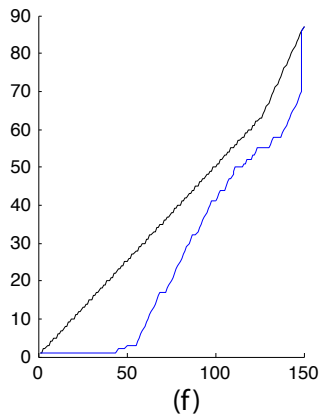
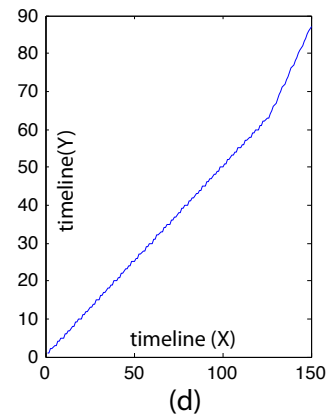
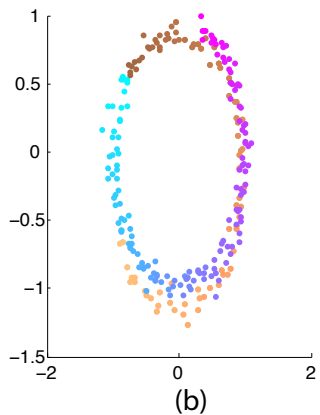
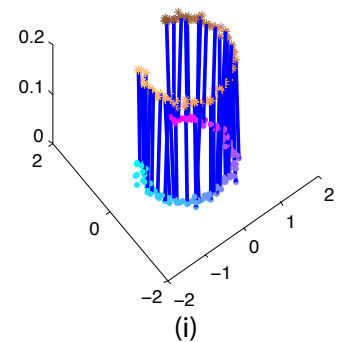
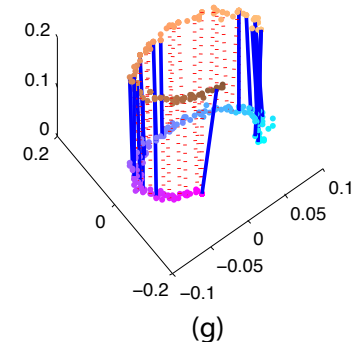
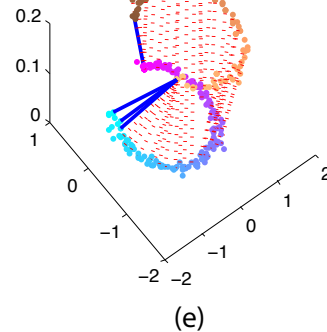
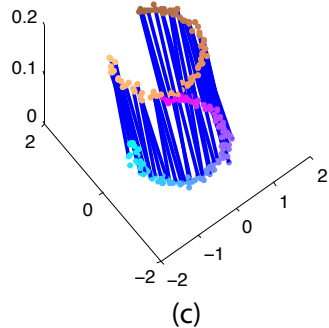
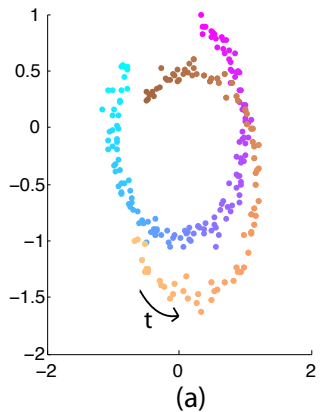
input : $\{X^k\}_{1 \leq k \leq K}$, initial template \tilde{Y}
output: new template Y and new warpings ϕ^k
for $1 \leq k \leq K$ **do**
 └ Compute warpings $\tilde{\phi}^k = (\tilde{\phi}^{k,x}, \tilde{\phi}^{k,y}, \tilde{m})$ between X^k and \tilde{Y} using DTW;
 Compute $\mu(t) = \sum_{k=1}^K \tilde{\phi}_t^{k,x}$, where $1 \leq t \leq \tilde{m}$;
 Define $Y_t = \sum_{k=1}^K Y_{(\tilde{\phi}^{k,x}(\mu^{-1}(t)))}$, where $1 \leq t \leq \frac{1}{K} \sum_{k=1}^K n_k$;
for $1 \leq k \leq K$ **do**
 └ Compute warpings $\phi^k = (\phi^{k,x}, \phi^{k,y}, m)$ between X^k and Y using DTW;

Algorithm 3. Multiple trajectories registration

input : $\{X^k\}_{1 \leq k \leq K}$
output: $\omega = \{R_k, T_k, \phi^k, Y \mid 1 \leq k \leq K\}$
 Y is initialized as the X^k with median length;
for $1 \leq k \leq K$ **do**
 └ $R^k = \text{Id}, T^k = 0$
repeat
 └ Update Y and $\{\phi^k\}$ using Algo. 2 with input $\{R^k X^k + T^k\}_{1 \leq k \leq K}$ and Y ;
 for $1 \leq k \leq K$ **do**
 └ compute R^k, T^k using rigid registration and correspondence set
 └ $\{(X_{\phi_t^{k,x}}^k, Y_{\phi_t^{k,y}}) \mid 1 \leq t \leq m_k\}$;
until C_{multi} converges ;

STW - Synthetic Experiments

Two synthetic sequences. Time is color coded.



(ICP)

(Ground truth)

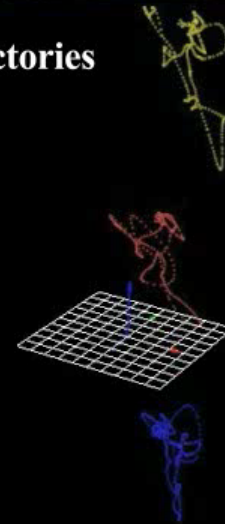
(DTW)

(CTW)

(STW)



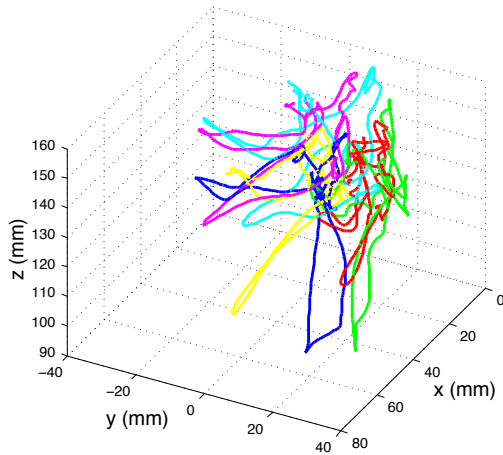
Left tool trajectories



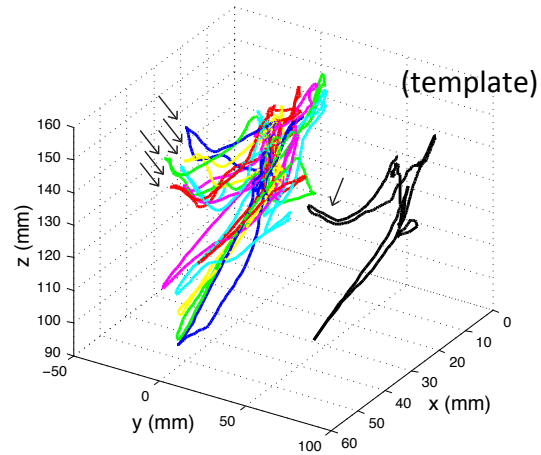
Spatio-Temporal Registration Demo - Nicolas Padoy, CIRL, JHU

[Padoy, Hager, MICCAI'11]

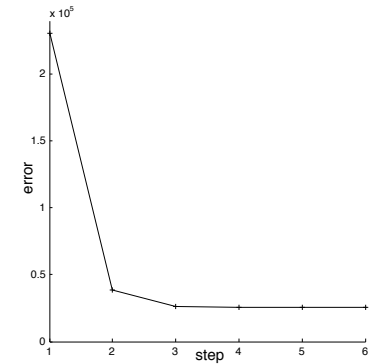
Results – Knot Tying Task



6 raw trajectories

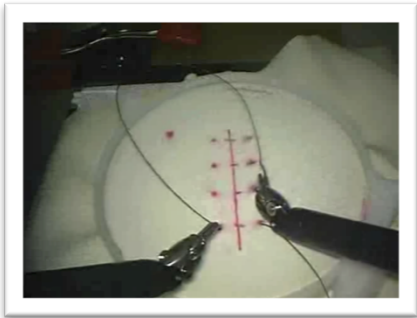


6 registered trajectories

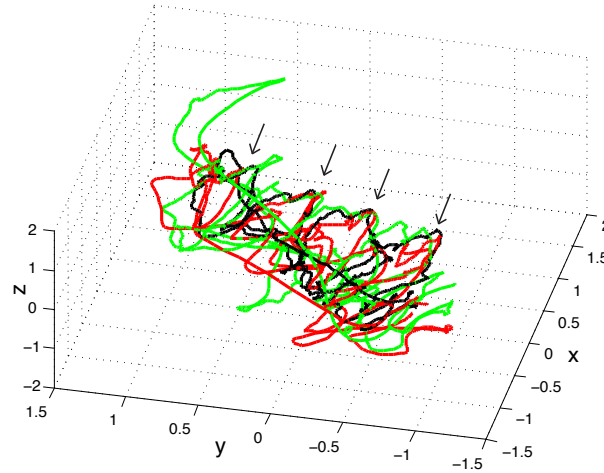


registration error

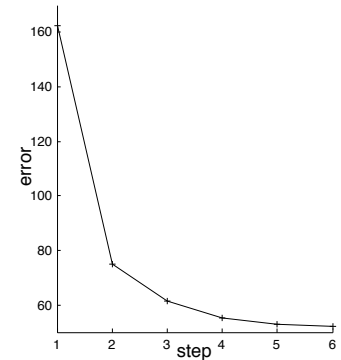
Results – 4-Throw Suturing Task



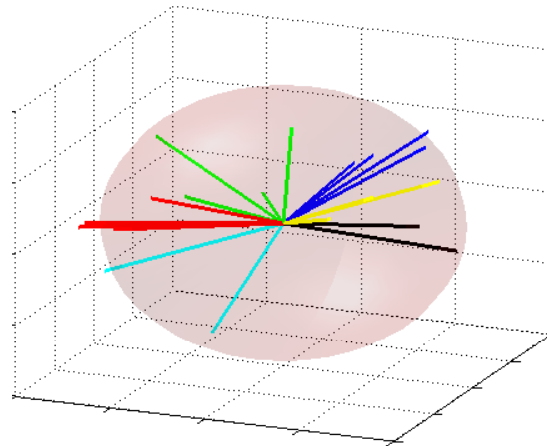
4-throw suturing tasks



3 of 19 registered trajectories

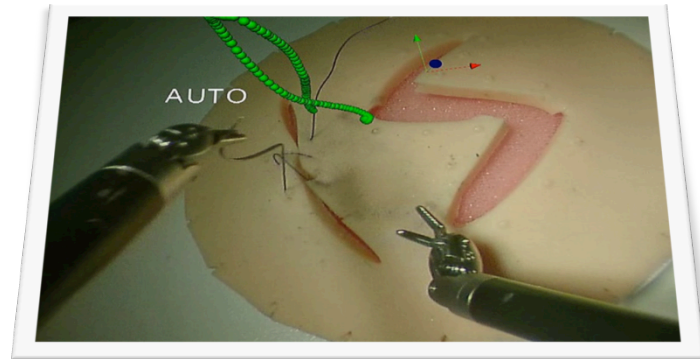


registration error

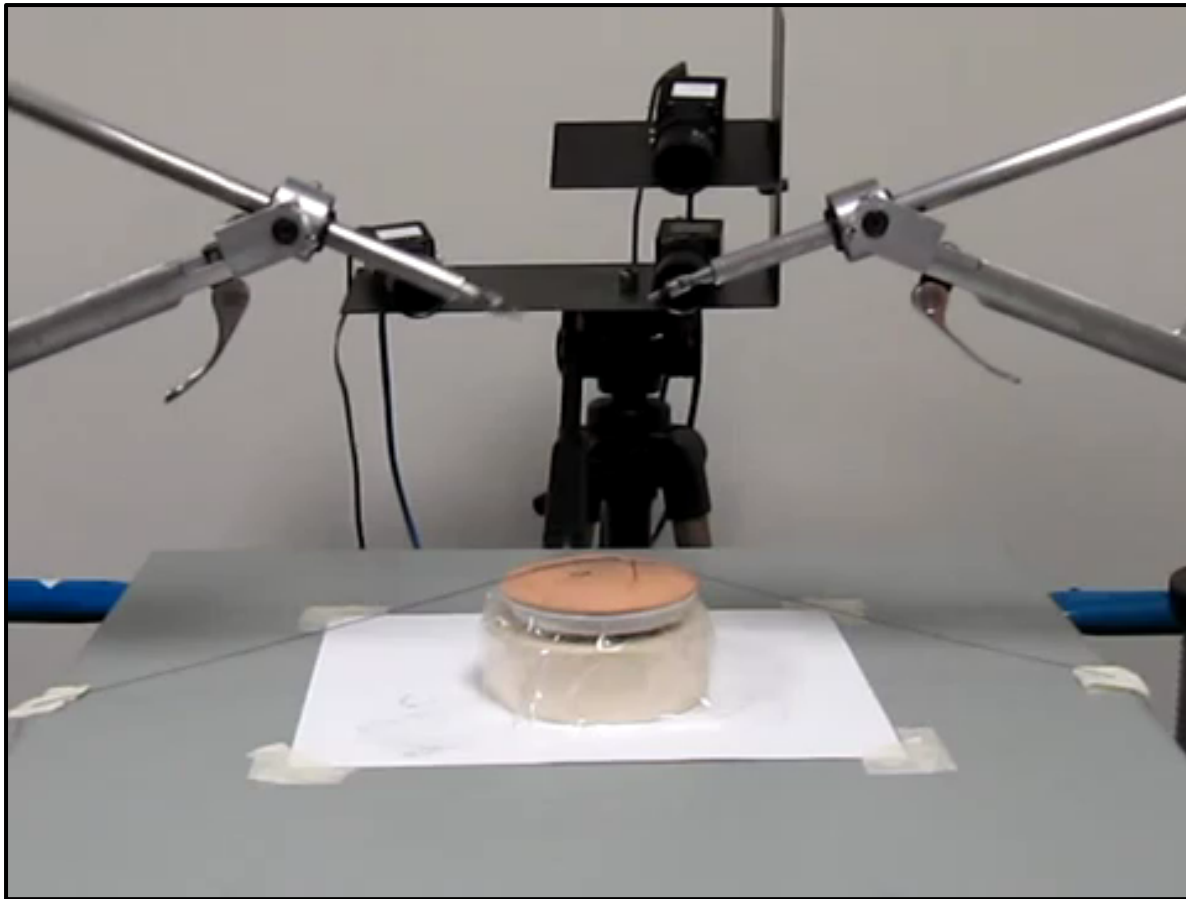


rotation axes colored per surgeon

Human-Machine Collaboration

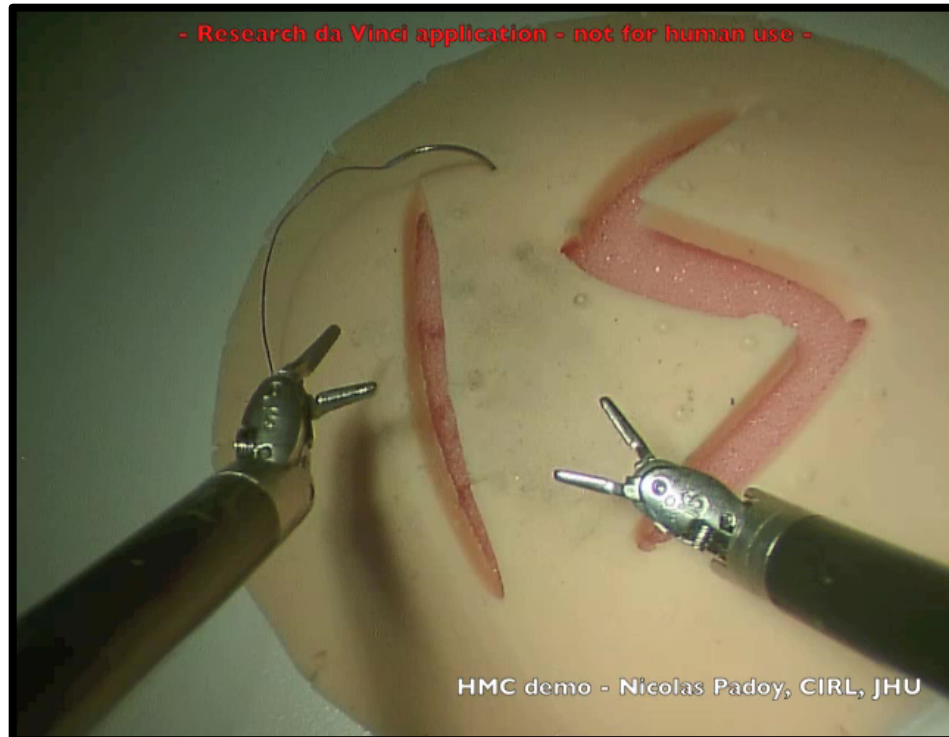


Beyond motion replay



[Superhuman Knot Tying, van den Berg, ICRA'2010]

Human Machine Collaboration

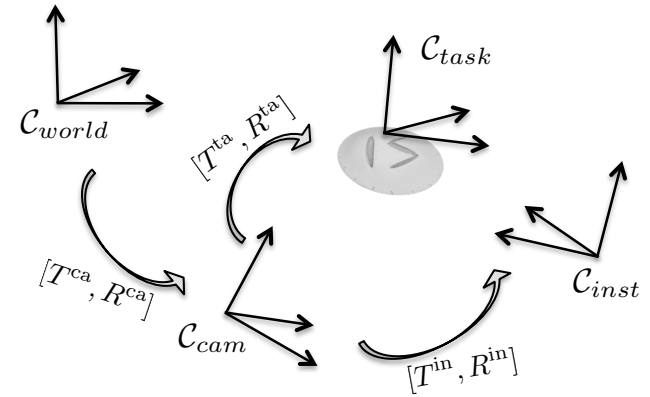
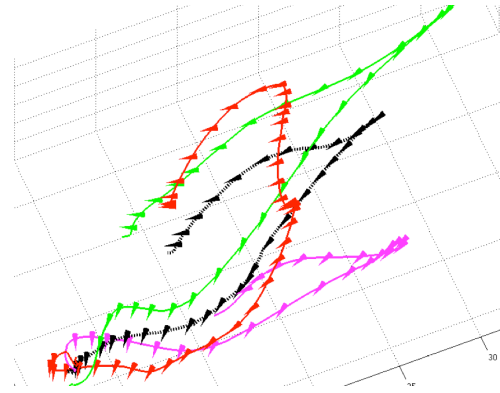
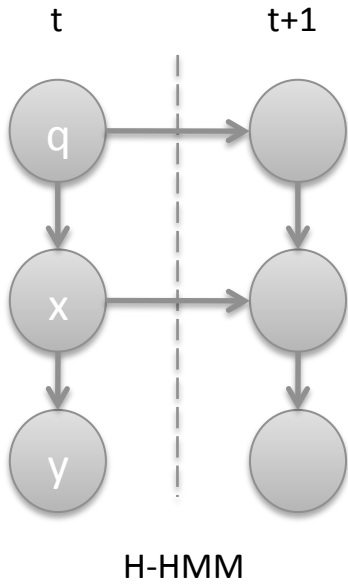


Padoy, Hager, ICRA 2011

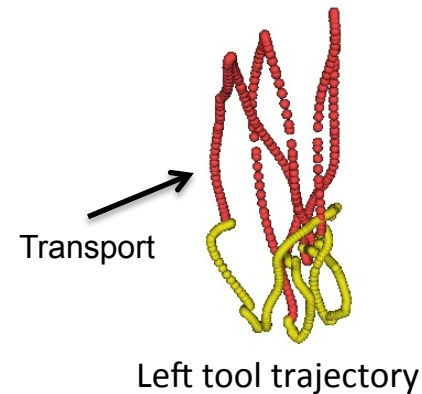
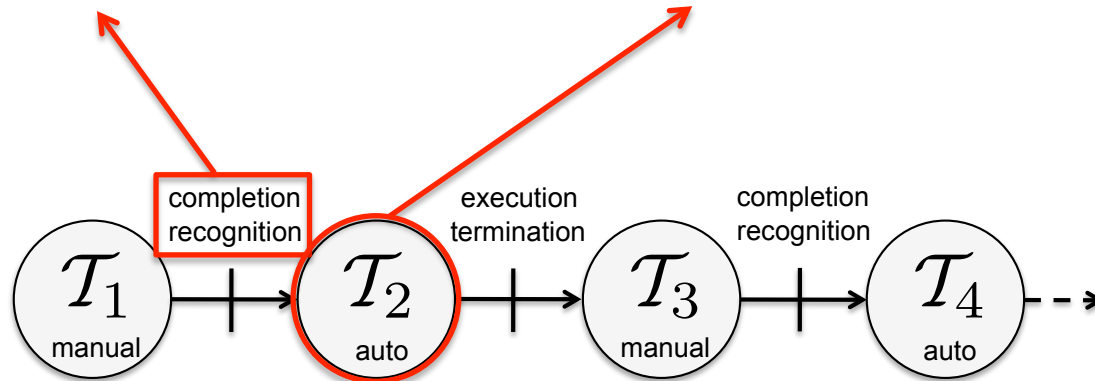
(patent pending)



Methods

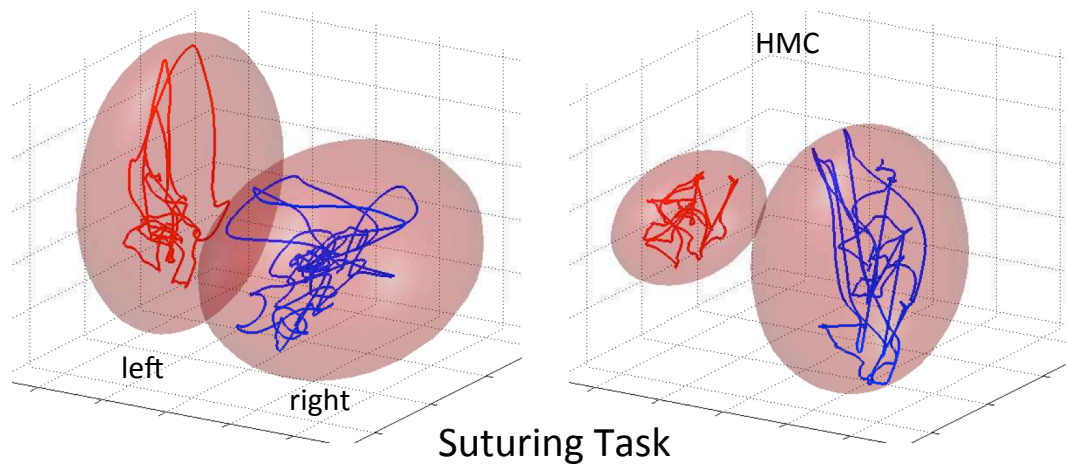


Temporal Motion Averaging + Robot Control



Results

- Reduced master manipulators motions



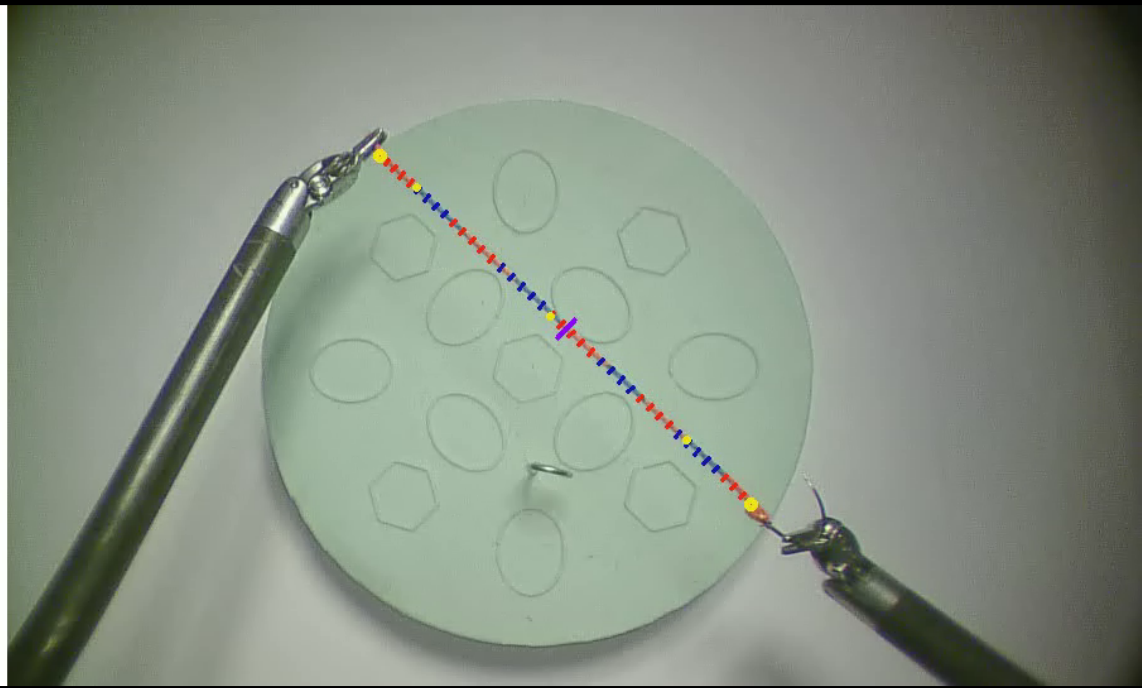
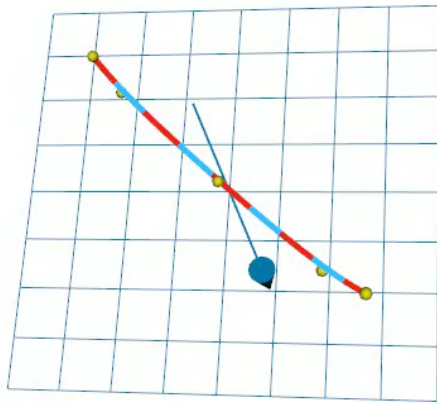
Suturing Task

- Shorter traveled distances

- Smaller standard deviations:

	Pin Task			Sut Task		
	x	y	z	x	y	z
Manual	55.4	50.4	22.1	17.7	21.4	38.3
HMC	10.6	19.9	23.1	12.1	16.7	23.2

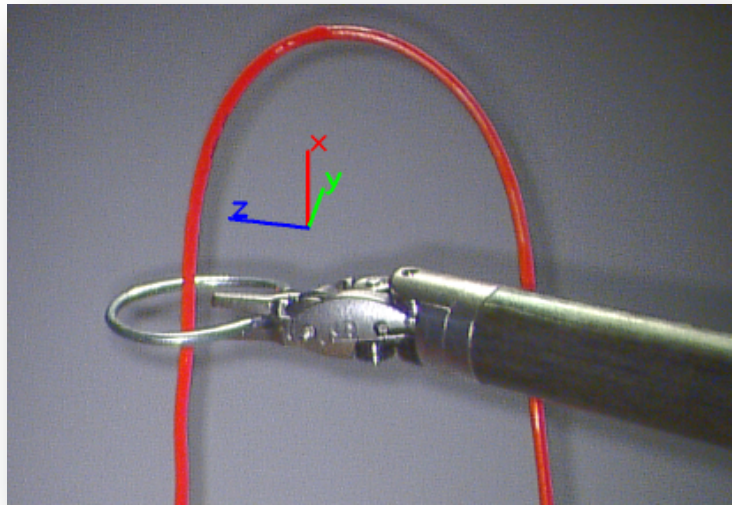
Need for Physical Context Tracking



Padoy, Hager, BMVC 2012

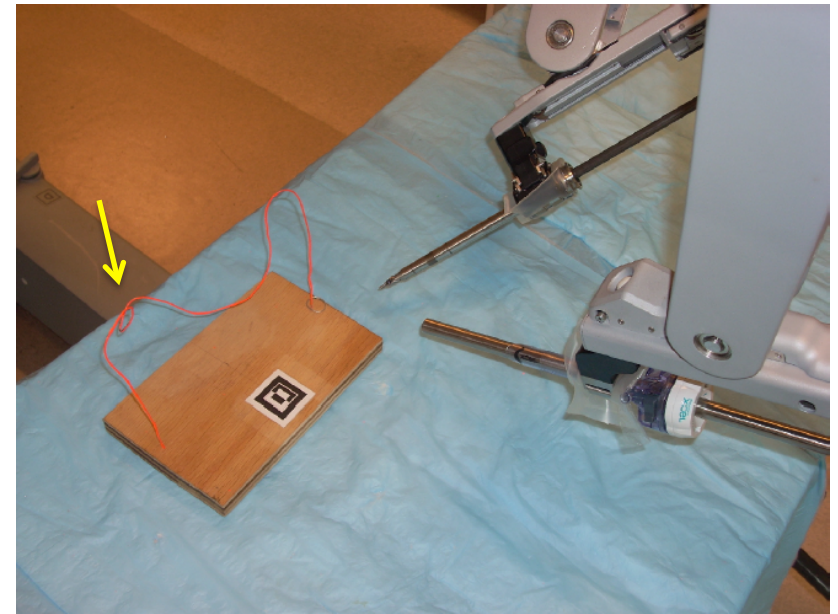
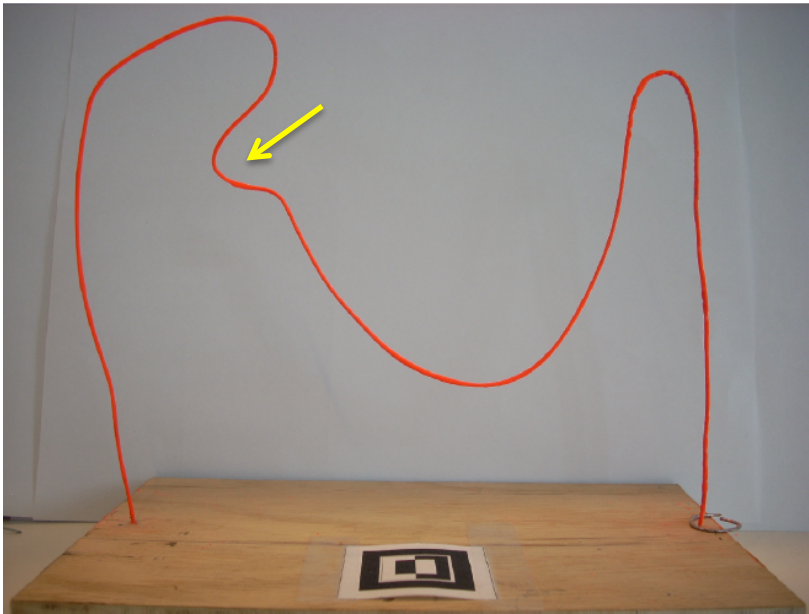
(patent pending)

Learning-based Partial Automation (does ergonomics matter?)



(In collaboration with Sebastian Bodenstedt, KIT)

Ring transfer task

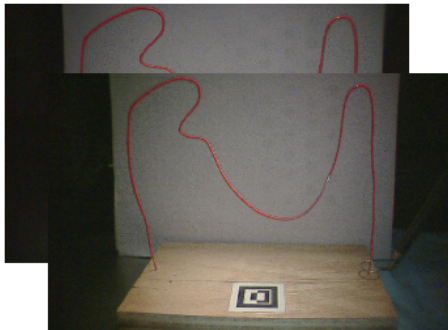
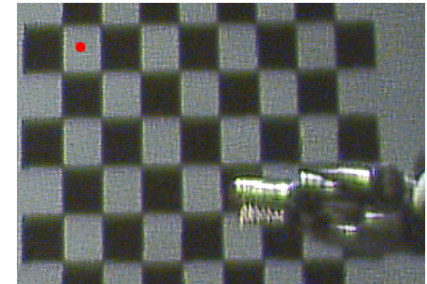


Partial automation of a dexterous task:

- Control position of the instrument through the user
- Control orientation of the tool through the robot

Model of the environment

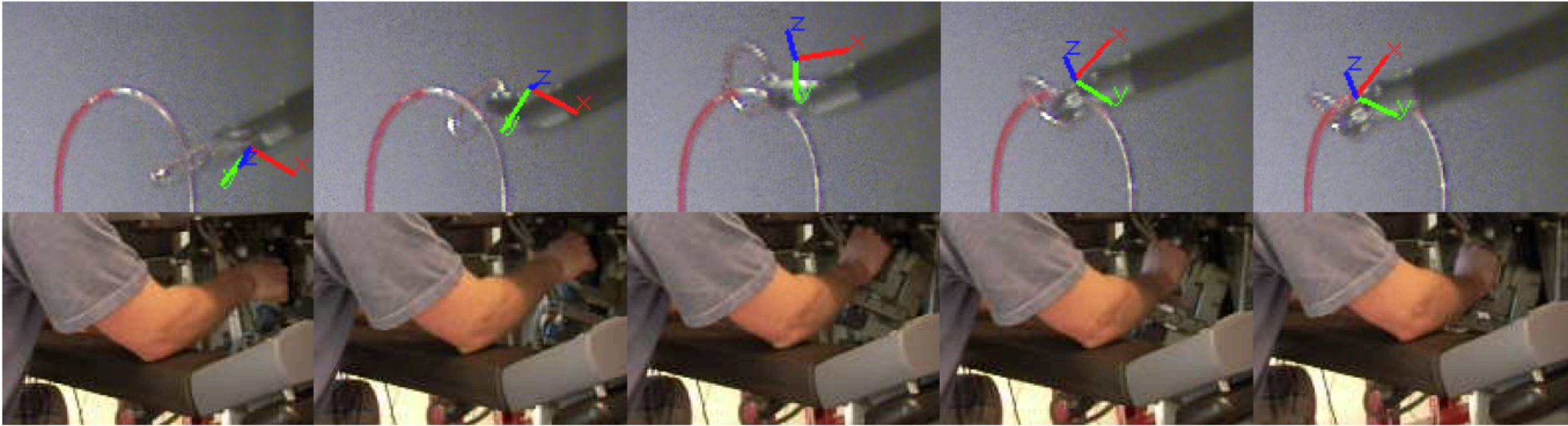
- Stereo endoscope calibration
 - 3D reconstruction error: 1.58mm
 - Rectification error: 2.43px
- Instrument position calibration
 - Correction with reconstructed chessboard pattern
- Model of the environment



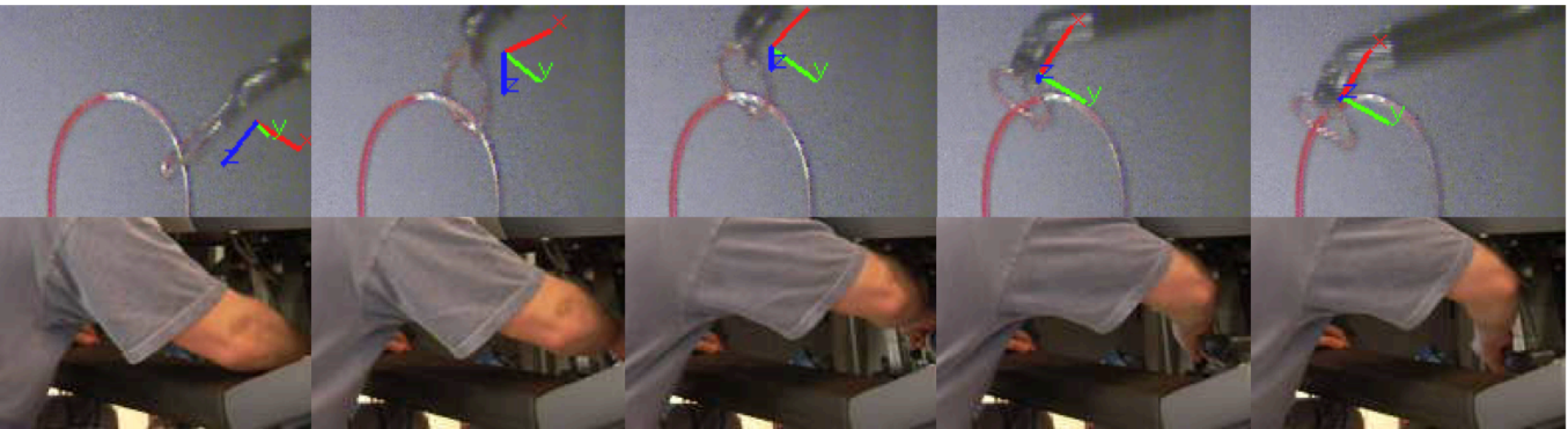
preprocessing + semi-global block matching

spline approximation

Comparison no automation / automated rotation



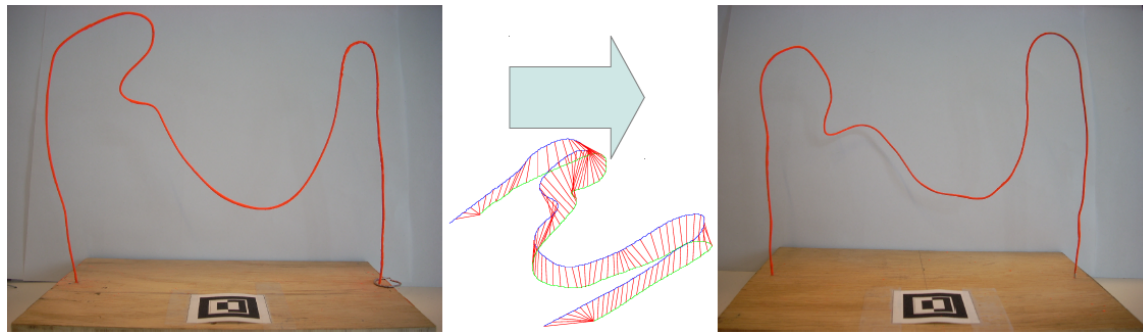
No automation



Automated rotation

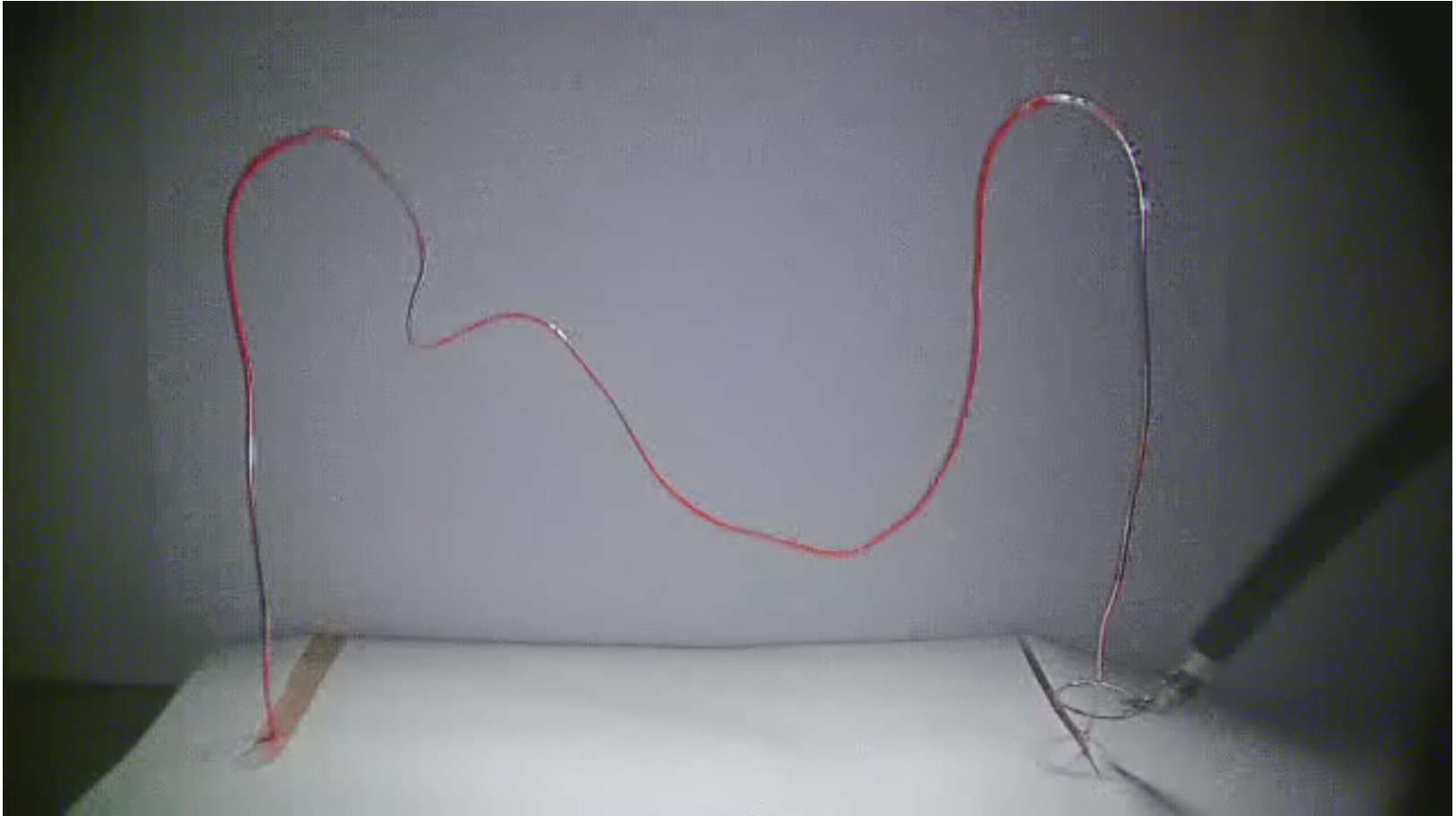
Solution

- Use Gaussian mixture regression (GMR) to learn ‘ergonomy’ from expert demonstration on a reference task
 - Learn conditional PDF $P(R|t)$
- Map current task to reference task using DTW



- Combine GMR, current position and 3D spline to infer automated rotation

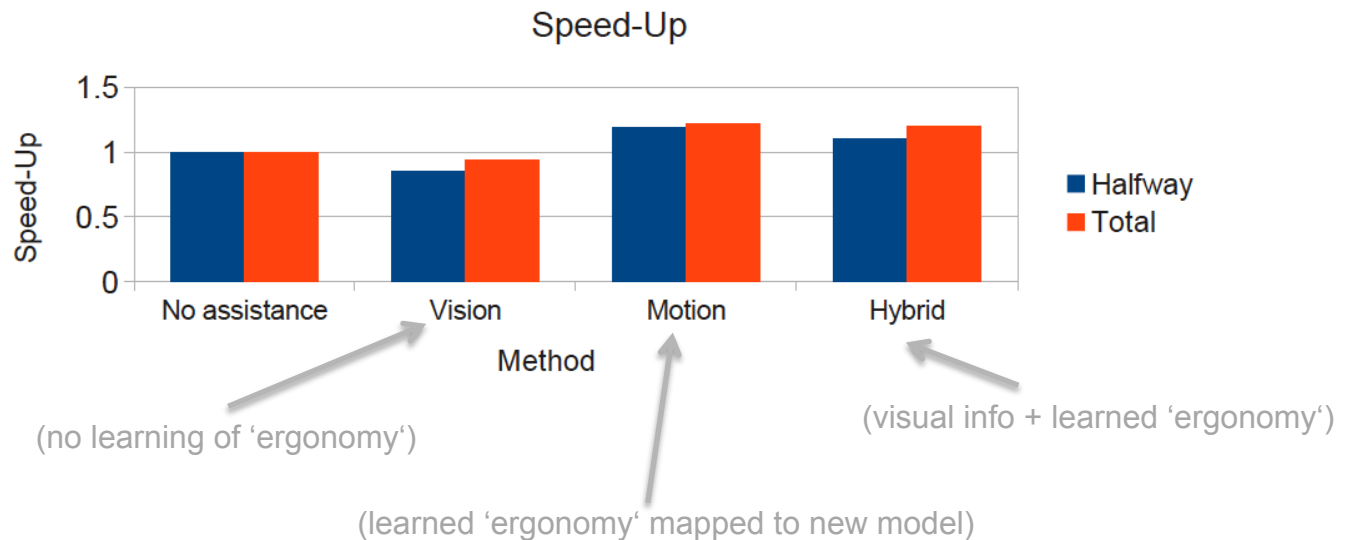
Video



Bodenstedt, Padoy, Hager, RLIHT 2012

User Study

- 10 participants
- 4 tasks per user (randomized order)



- Larger speed-up on beginners
- Hybrid method ranked best, vision method ranked worst

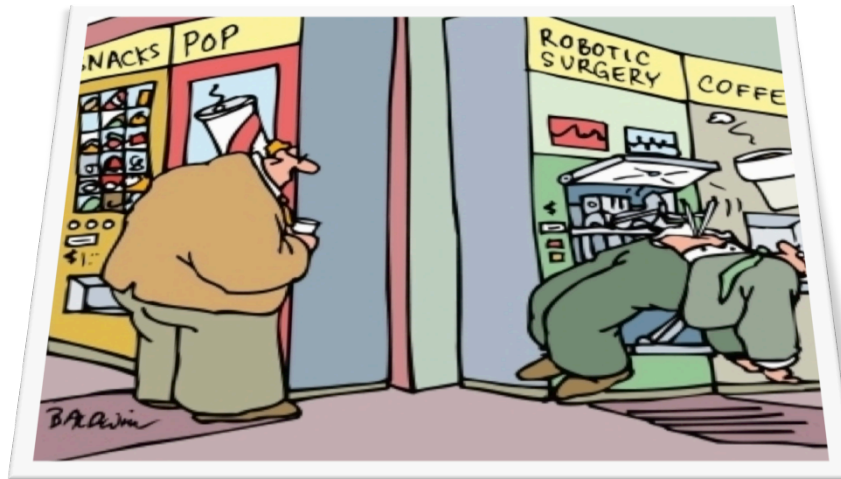
Conclusion

- Trajectories are not sufficient
- Models of tool/tissue and operator/tool interactions needed



MIX-Surg

Thank you for your attention !



Spatio-temporal Registration of Multiple Gestures for Skills Analysis and Automation in Robotic Surgery

Nicolas Padoy

University of Strasbourg, France

