



Human-Supervised Manipulation of Deformable Objects

Next Generation Collaborative Medical Robotic Systems Towards Intelligent Robotic Surgical Assistants

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Human-Supervised Manipulation of Deformable Objects

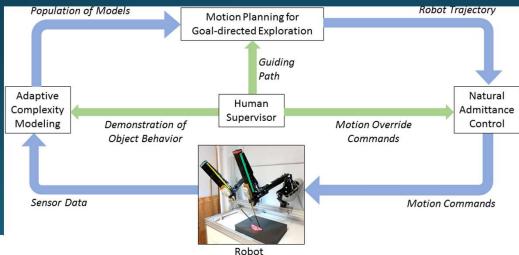
Goal:

 Develop algorithms that enable human-supervised robotic manipulation of deformable objects under substantial uncertainty

Research Thrusts

- Modeling: Modeling deformable object dynamics and associated uncertainty,
- Planning: Planning algorithms for integrated exploration and task execution,
- Control: Control algorithms for robust manipulation of deformable objects under uncertainty,

 Human Supervision: Algorithms for effective human supervision of robotic manipulation of deformable objects







Intelligent Robotic Surgical Assistants

GOAL: Robotic system to act more like an assistant and less like a follower

- Provide robotic surgical systems with low-level task automation capabilities
- Surgeon will have a high-level interaction with the system rather than low-level direct teleoperation
- System assist in basic manipulation tasks, such as, retraction, dissection, exposure, suturing
- Reduce tedium from simple, repetitive tasks; assist in complex manipulation tasks; reduce cognitive load





Research Focus

 Low level surgical manipulation capabilities for delicate deformable objects

Target tasks:

- Retraction
 - Key skills / algorithms for manipulation of deformable objects
- Surgical suturing + knot tying
 - Arguably most complex dexterous bimanual manipulation task in minimally invasive surgery





Research Focus



Perception

- Estimation of deformable object boundary constraints and material parameters
 - For simultaneous manipulation and planning
- Localization and tracking of surgical thread, needle, and tools
 - For vision based control
- Needle-tissue interaction force state estimation
 - For force based control

Planning

- Needle path planning
- Optimal needle grasp and entry port planning
- Dual-arm needle manipulation planning

Control

- Visually-guided manipulation
- Knot tying





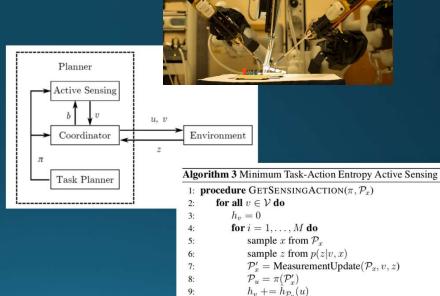
Task Action Entropy Based Active Sensing

Research Challenges

- Planning under uncertainty
 - POMDP general but online solution not practical for high dimensional systems
- Decouple state estimation from planning
 - (Active) sensing for state estimation
 - Belief state planning
- Active sensing for state estimation answers "Where am I?" rather than "Do I know what to do next?"

Approach

- Control actions partitioned to sensing actions and task actions
- Sensing actions are chosen to minimize the conditional entropy of future task actions



end for

13: end procedure

return argmin, h_v





Dynamic Tracking of Surgical Threads

Research Challenges

- Tracking of one dimensional deformable objects
- Computationally efficient algorithm for use in visually guided control
- Not rely on detailed a priori knowledge of parameters and material properties
- Handle complex topology, such as, overlaps and knots

Approach

- The suture thread is modeled as a NURBS curve
- Image segmented using a thin feature extraction method which identifies local thread direction
- The model is projected into stereo image space
- The model deforms using image energy
- The model tracks the suture thread in real-time

Now that the NURBS model has been initialized, it actively tracks the suture thread during motion.





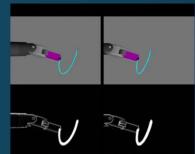
Dynamic Tracking of Surgical Needle

Research Challenges

- Success of needle driving task relies heavily on the accuracy of needle grasp
- Substantial uncertainty in a priori needle pose
- Frequent occlusions with tools and tissue
- Computationally efficient algorithm for use in visually guided control

Approach

- Vision-guided Bayesian state estimation from stereo endoscopic image streams
- Image segmented using a thin feature extraction methods
- Kinematic information of the tools provides needle motion prediction
- The model is projected into stereo image space
- Image space similarity measure
- Needle pose is tracked in real-time





Needle Grasping Task



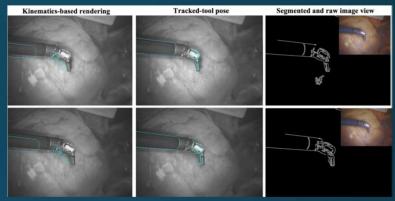


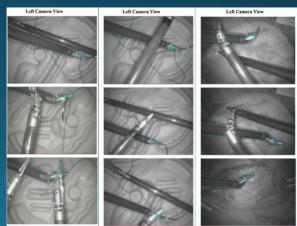
Dynamic Tracking of Robotic Surgical Tools

Research Challenges

- Uncertainty in hand-eye (i.e., robot-camera) calibration
- Frequent occlusions of tools
- High dimensional state estimation problem
- Computationally efficient algorithm for use in visually guided control

- Vision-guided Bayesian state estimation from stereo endoscopic image streams
- Kinematic model of the robotic system provides tool motion prediction
- Image space similarity between the predicted tool image and the observed image







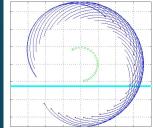


Needle Path Planning and Control

Research Challenges

- Minimize tissue tear and trauma
- Substantial uncertainty in geometry
- Needle sweeps out an area that create internal tissue stresses
 - No direct way of measuring due to cutting and friction forces

- Modeling of interaction forces
 - Computationally efficient for real-time planning and control
- Unscented Kalman Filter to estimate different force components
- Select needle driving trajectories that minimize tissue tearing forces

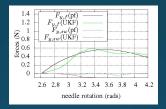


$$\begin{split} \mathbf{f}_{needle}(\phi(t)) &= \mathbf{f}_{friction}(\phi(t)) \\ &+ \mathbf{f}_{cutting}(\phi(t)) + \mathbf{f}_{normal}(\phi(t)) \end{split}$$

$$\mathbf{f}_{friction}(\phi(t)) = \int_{\theta_0(\phi)}^{\theta_1(\phi)} -\mu_s \mathrm{d}\ell(\theta) \,\mathrm{d}\theta$$

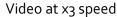
$$\mathbf{f}_{normal}(\phi(t)) = -\mathbf{K} \int_{\phi(0)}^{\phi(t)} \int_{\theta_0(\phi)}^{\theta_1(\phi)} \mathrm{d}\mathbf{a}_n(\phi,\theta) \, \mathrm{d}\theta \, \mathrm{d}\phi.$$

$$\mathbf{f}_{cutting}(\phi(t)) = -\min(\alpha, (\theta_{tip} - \theta_s)^2 \beta) d\ell(\theta_{tip})$$











Needle-Tissue Interaction Force State Estimation

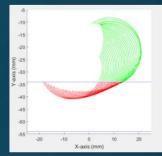
Research Challenges

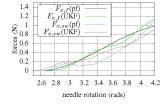
- Successful needle drive minimizes tissue trauma
- As needle moves through the tissue it sweeps out an area that create internal tissue stresses
- No direct way of measuring tissue deformation forces, as force sensor data will also include cutting and friction forces

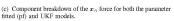
Approach

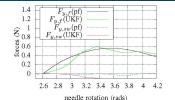
- Unscented Kalman Filter to estimate different force components
- Validated using experiments with phantom and ex vivo tissue



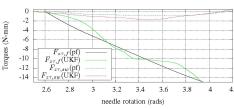








(d) Component breakdown of the \boldsymbol{y}_n force for both the parameter fitted (pf) and UKF models.



(e) Component breakdown of the $z\tau$ torque for both the parameter fitted (pf) and UKF models.



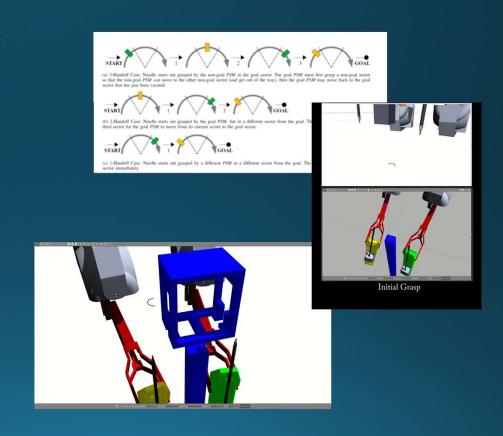


Dual-Arm Needle Manipulation

Research Challenges

- Needle grasping and re-grasping requiring multiple needle handoffs
- Each handoff introduces uncertainties
- Limited workspace

- Hybrid state space motion planning using RRT
- Visual guidance coupled with local partial replanning







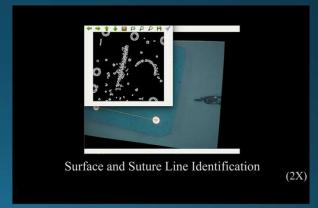
Visually-Guided Manipulation

Research Challenges

- Managing uncertainties
- Minimize real-time sensory feedback
- Limited calibration

- Supervisory control
- Model-based tracking of key
- Vision-guidance at key steps









Next Steps



- Further advances in task automation
 - More tightly integrated perception+planning+control
 - Planning of more complex manipulations
 - Compliant motion control based manipulation algorithms
- More complex manipulation tasks
- Effective user interfaces
- Implementation on the dVRK system and open source release of the algorithms





