Project Checkpoint Presentation:

Optimized Tissue Structure Modeling

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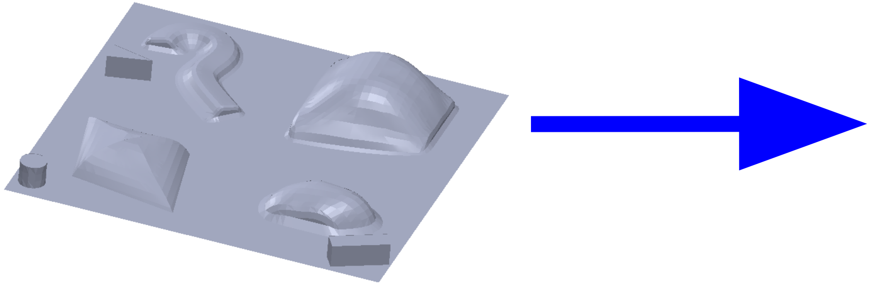
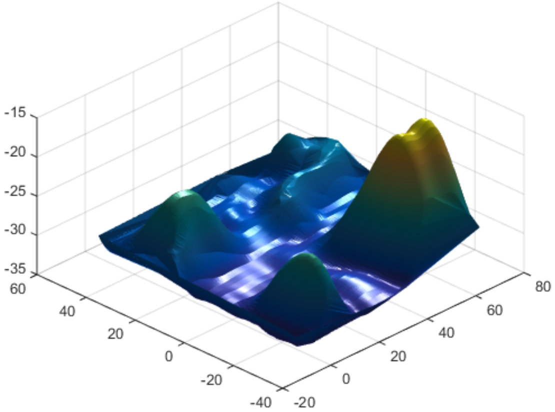
Presentation Outline

- Background/Project Design
- Completed Work
- Dependencies/Problems
- Future Projections

Optimized Tissue Reconstruction

Accurately reconstruct a tissue/surface from finite number of force sensor palpation readings

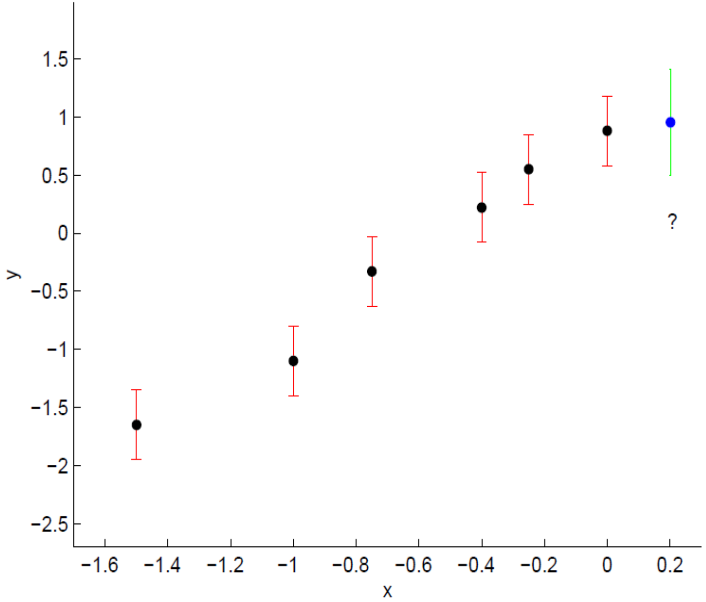




Background/Project design	Completed Work	Dependencies/Problems	Future Projections

Tissue Reconstruction: Gaussian Process

- A Gaussian Process (GP) is a collection of random variables that have joint gaussian distributions
- For tissue reconstruction:
  - Model each force sensor palpation reading as gaussian distribution and then compute gaussian process of al palpation readings
  - Use gaussian process to model interpolated points within tissue rang



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Tissue Reconstruction: Gaussian Process

$$\hat{y} = Cov(t,\tilde{x}) * Cov(t,t)^{-1} * y(t)$$

$$\sigma_{\hat{y}}^2(\tilde{x}) = C(\tilde{x},\tilde{x}) - Cov(t,\tilde{x}) * Cov(t,t)^{-1} * Cov(t,\tilde{x})$$

Use these equations to model tissue after testing n points

- The next algorithmic step is to select the (n+1)th point to test
  - We will later discuss methods for optimally selecting the (n+1)th point

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Geometry reconstruction through batch process

- For simplicity, we first implemented a GP with the purpose of reconstructing a digital phantom
- To further simplify the process, a batch process was used
    - There was no optimal selection of an (n+1)th point
    - Instead, 1.2% of the pixels were sampled and used for the training set

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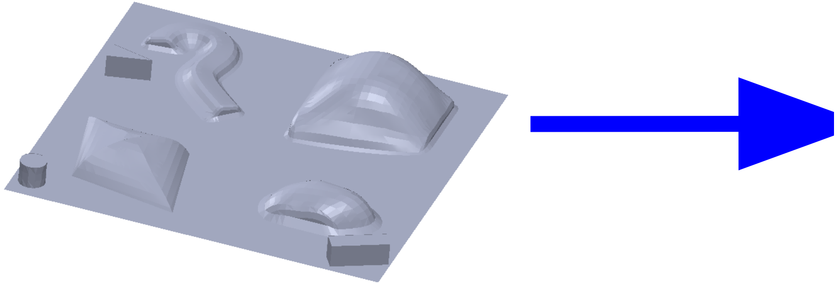
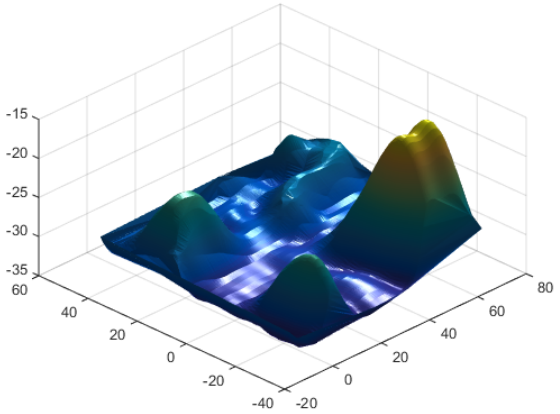
Geometry reconstruction through batch process





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Online GP Regression Pseudocode

while (n < max_number_points_tested) {

- Train GP on n points
- pick (n+1)th point
- Train on (n+1) points

}

predict values (reconstruction)

Methods for picking the next point

1. Randomly Choose The Next Point
2. Choose the next point with the highest predicted variance, Active Learning McKay (ALM)
3. Choose the next point with the largest predicted effect on the GP, Active Learning Cohn (ALC)

Methods for picking the next point

1. ~~Randomly Choose The Next Point~~
2. Choose the next point with the highest predicted variance, Active Learning McKay (ALM)
3. Choose the next point with the largest predicted effect on the GP, Active Learning Cohn (ALC)
   - Two versions implemented (ALC-mean and ALC-max)

ALM vs ALC Results

ALM

Predict the variances of n random points and choose the point with the highest variance as the next point to train on.

ALC-mean

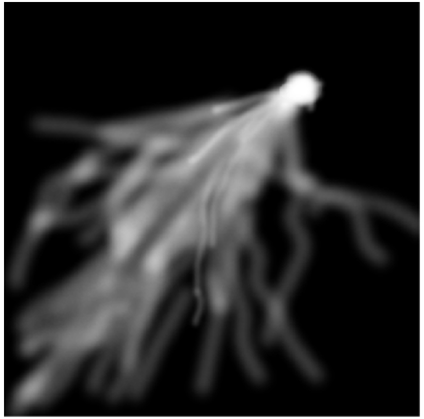
Predict the change of the variance of n random points at should each of these n random points be added to the training set.
Choose the point with the largest mean change in variance.

ALC-max

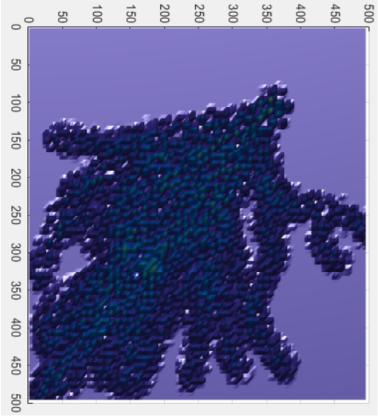
Predict the change of the variance of n random points at should each of these n random points be added to the training set.
Choose the point with the largest maximum change in variance.

ALM vs ALC Results

Actual

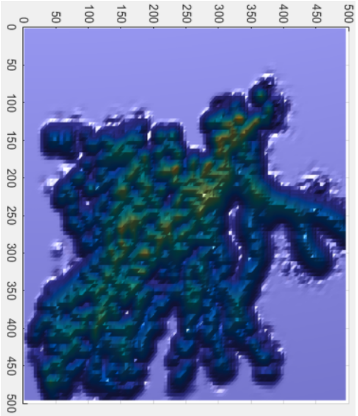


ALM



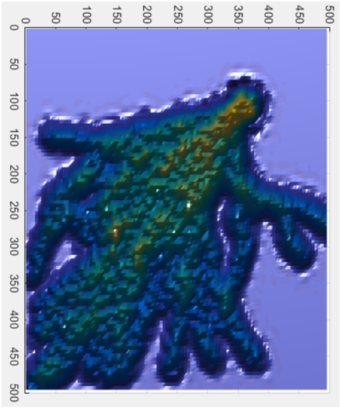
MSE: 2913.6
SD: 44.9

ALC-mean



MSE: 1041.2
SD: 29.5

ALC-max



MSE: 227.1
SD: 13.5

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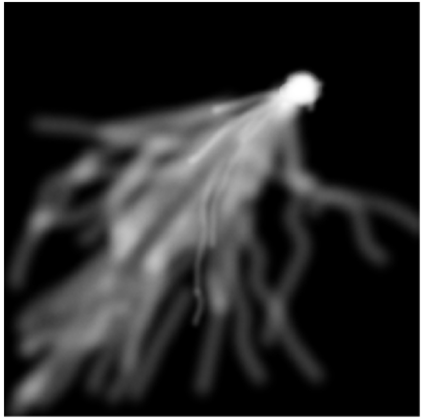
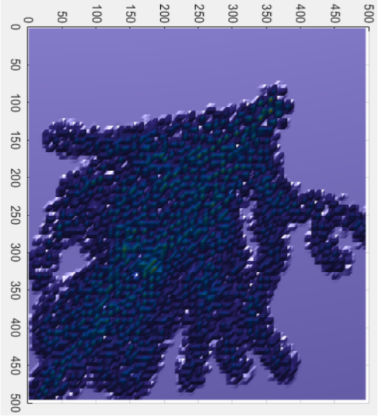
ALM vs ALC Results

Actual



ALM



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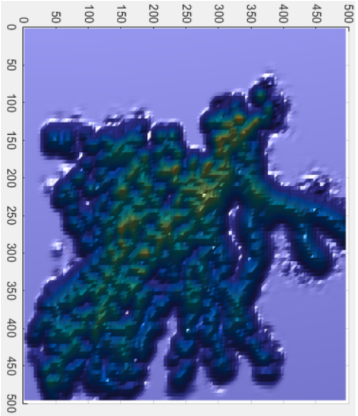
ALC-mean



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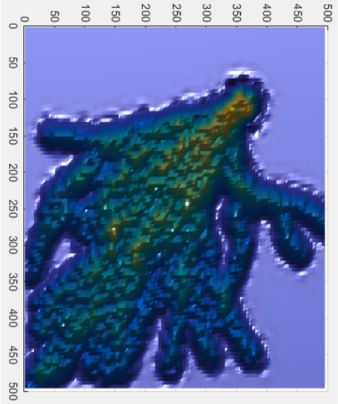
ALC-max



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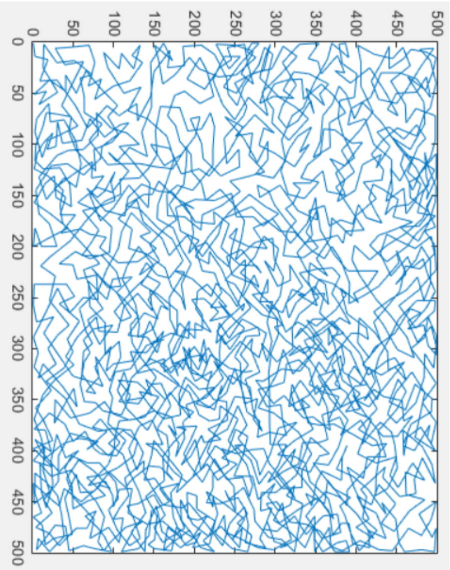
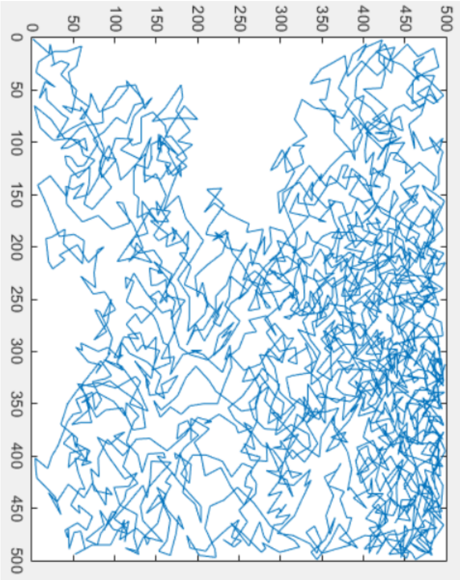
ALM vs ALC Paths

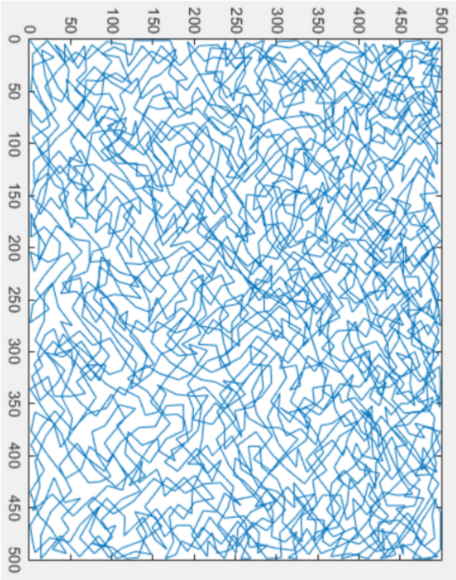
ALM



ALC-mean



ALC-max



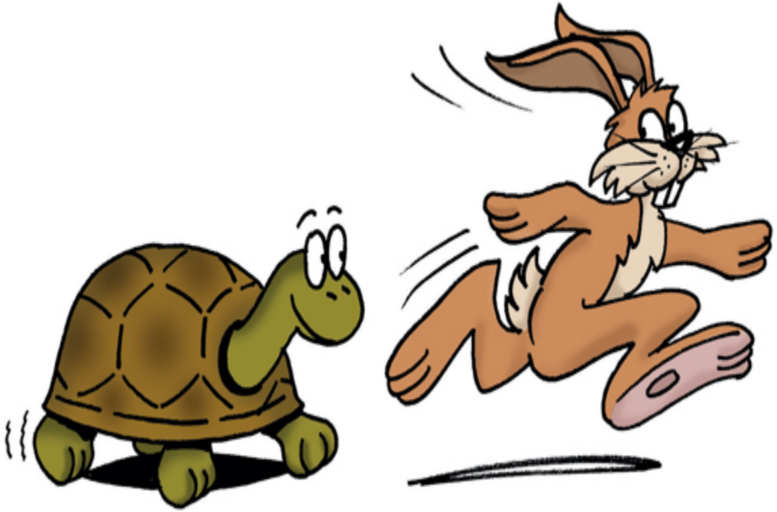
Background/Project design	Completed Work	Dependencies/Problems	Future Projections

Dependencies

- The force sensor has arrived (no longer a dependency)
- Need 1 day to test cartesian stage with Preetham
    - Will happen this week
- Access to mentors for guidance on stiffness model (will discuss more later)
- Phantoms of various shapes (Preetham)

Problems

- Algorithm efficiency
  - When covariance matrix becomes large, our GP algorithm becomes incredibly slow



Tortoise
(large cov. matrix)

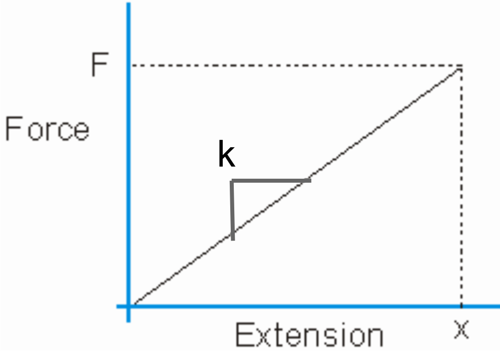
Hare
(Small cov. matrix)

Future Work

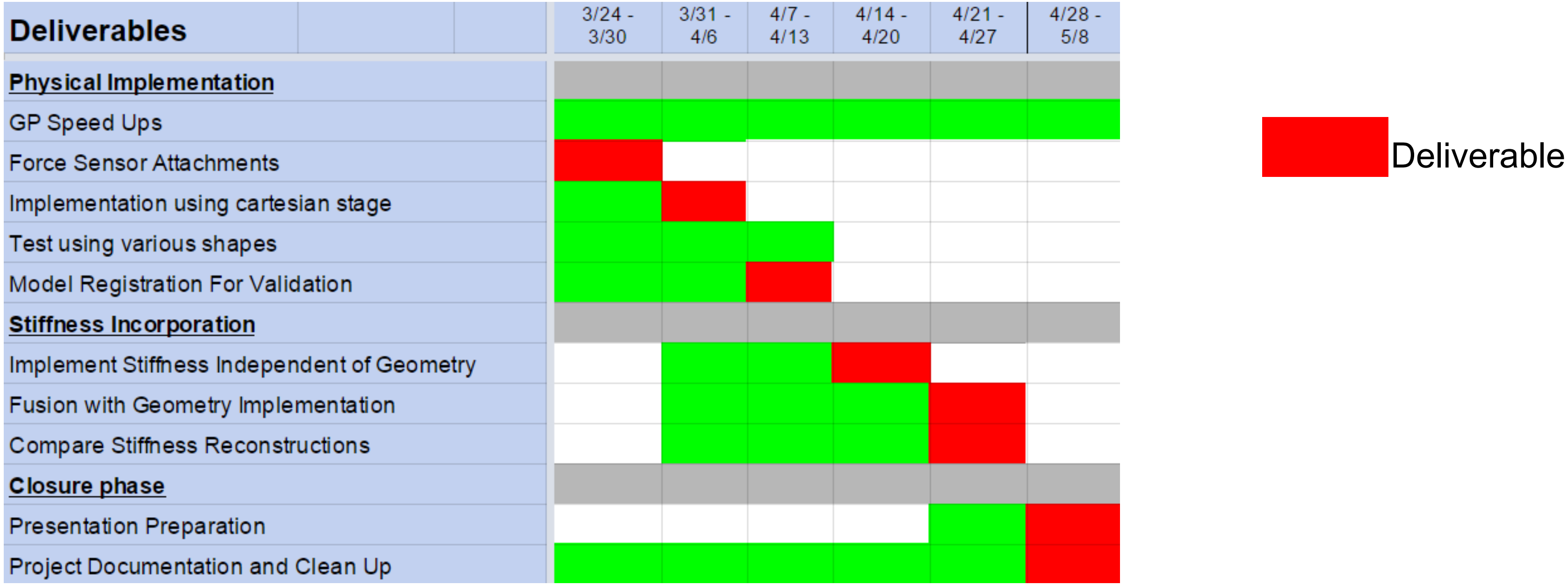
- Real World Testing
- Incorporation of Stiffness
- Efficiency Improvements
    - Rank+1 Cholesky Decomposition Updating
    - Implement distributions or methods which utilize smaller covariance matrices. These would compare points to nearby points instead of points in the entire model.

Stiffness incorporation plan

1. Create GP for stiffness that is independent of geometry reconstruction GP
   a. Stiffness GP will utilize force sensor data according to hooke's law: k = F/x
2. Update stiffness GP to utilize geometric information
   a. Stiffness and geometry are not independent variables



Updated Timeline



Deliverables

- ✓ **Minimum:** Geometry reconstruction of a sample image using Gaussian process
- **Expected:** Geometry reconstruction of sample tissue using Gaussian process ✓
  - Utilize cartesian stage
- **Maximum:** Using geometry reconstruction of sample tissue, create model of stiffness within tissue

Questions?