Team 10: Optimized Tissue Structure Modeling

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Introduction/Background:

The motivating goal for this project is to quickly and accurately reconstruct a three-dimensional model of a tissue based off of recordings from a finite number of force-sensor palpations. We plan to write an algorithm that will interpolate the height (z) values of all (x,y) positions within the range of the tissue based off of a finite number of readings from the force-sensor. It is important to note that we will be using the force sensor as a measure of height and in doing this, there will be some variance from those readings.

There are many ways to interpolate values based off of sample values. We plan to utilize the method of gaussian process regression in order to do this. Most generally, a gaussian process is a multivariate gaussian distribution. We will model each force-sensor palpation reading as a gaussian distribution, and all of the gaussian distributions (one for each force sensor reading) combined represents the gaussian process. We will then use the computed gaussian model to predict the interpolated points within the tissue range. Using a probabilistic model such as a gaussian processes has various advantages over non-probabilistic models (such as polynomial fitting). The most notable advantage being gaussian processes output a variance for each interpolated point. Knowledge of variance is essential for any type of model related to human health. The variance will give you insight in how much you can actually trust your model.

From a computational perspective, gaussian processes rely on the covariance function, k(x_i,x_j).[1] That is the covariance function for two points, x_i and x_j that have outputs y_i and y_j. There are many covariance functions and we plan to experiment with several different types to determine which one is most appropriate for our system. A commonly used one (and the one we will start with) is called the "squared exponential". Now imagine there are n recorded points such that their position can be expressed as $x = [x\_1 \quad ... \quad x\_n]$ and output can be expressed as $y = [y_1 \quad \cdots \quad y_n]$ The first computational step is to compute all possible covariance functions for n recorded points such that:

$$K = \begin{bmatrix} k(x_1, x_1) & \cdots & k(x_1, x_n) \\ \vdots & \ddots & \vdots \\ k(x_n, x_1) & \cdots & k(x_n, x_n) \end{bmatrix}$$

Then, for each interpolated point (x*) within the tissue range compute:
$K^* = [k(x^*, x_1) \quad ... \quad k(x^*, x_n)]$ and $K^{**} = k(x^*, x^*)$
Using these values, we can compute the best estimate of the mean and variance of the output of each interpolated point (y*) within the tissue range according to the Gaussian process. The mean will be: $y^* = K^* K^{-1} y$ and the variance will be $Var(y^*) = K^{**} - K^* K^{-1} K^{*T}$.[2c]

As our model is to be utilized in real-time, our project also includes developing an algorithm to determine the optimal trajectory of palpations. By optimal trajectory, we mean finding the point that if palpated next will most likely minimize the variance present within the model. The cross entropy method will be used to determine the point that will minimize the variance within the model.[5] We are currently uncertain of all of the mathematics driving the cross-entropy method, but as detailed in our time-line we will have this figured out within the next week.

An overview of the broad-strokes (pseudocode) of our projected target software will be as follows. A rough estimate of the shape of the surface being modeled will be initialize. Now, the following steps will iteratively occur while the mean variance within the model is above a certain threshold. The next optimal point will be palpated and modeled as a gaussian distribution. The gaussian process will be calculated and the interpolated points will be modeled within the tissue range. Then the cross entropy method will be used to determine the next optimal point. Then the iteration will repeat.

We will experimentally test this algorithm using a cartesian stage within the robotorioum. The stage will have a force-sensor mounted to it. We will use a phantom as a sample tissue to model. We can also use various foam shapes a sample tissue.

A major down-stream goal of this project is to incorporate stiffness into this model. A stiffness prediction at each point within the tissue range would provide the end-user with a more comprehensive and informative model of the tissue. This would be implemented by taking the geometry reconstruction as the truth, and then performing another gaussian process and cross entropy method on the tissue stiffness. However, according to Professor Kobilarov it is unlikely we will achieve this step within our semester.

A major potential medical application of this project is guiding exploratory surgeries. This algorithm would allow for accurate, real-time localization of tumors. Additionally, after finding the tumor, this model could guide the surgeon to remove the tumor using computer vision techniques and virtual fixtures.

Deliverables:

- **Minimum:**
  Implemented algorithm in Matlab which can accurately reconstruct the geometry of 3 Dimensional model using gaussian process and cross entropy optimization.
  Although not a very ambitious deliverable we can deliver this even if something should happen to the force sensor for the cartesian stage(see dependencies below.
- **Expected:**
  An implemented algorithm in Matlab which accurately reconstructs both the 3 dimensional geometry of a phantom as well as the stiffness of the phantoms surface using gaussian process and cross entropy optimization. This implementation will include the required code to link up with a cartesian stage.
- **Maximum:**
  An implemented algorithm in C++ which satisfies the expected deliverable as well as functioning in real time as well as an evaluation of the best method to incorporate stiffness reconstruction.

Dependencies:

- Force Sensor: We need to pursue the company currently repairing it to get it back in a timely manner.

Expected Resolution: 3/3/15

- GalilTools: We need access to this or similar software as part of the cartesian stage manipulation. We are relying on Preetham for this.
  Expected Resolution: 3/3/15
- PC for Cartesian Stage: We are relying on a PC to be purchased or borrowed for the cartesian stage. If we cannot acquire one we will use our own.
  Expected Resolution: 3/9/15
- Access to Expertise: We are relying on access to expertise for both the robotics aspect of this project as well as the theory when needed. Our resolution beyond the reading lists and self teaching is meeting with our mentors, Dr. Kobilarov biweekly and Preetham weekly at 4:30.
  Expected Resolution: Ongoing

Timeline:

2/20 - Project Proposal Write Up
2/18-2/20 - Existing Code and Theory Familiarization
2/24-3/10 - GP in 3D
3/10 - Complete GP in 3D
3/3-3/13 - Complete GP/CEO in 3D
3/1-3/13 - TCP/UDP Socket to Cartesian Stage
3/13 - Working TCP/UDP Socket
3/13-3/31 - Testing and Iteration on algorithms using Cartesian Stage
3/31 - Functional Geometry Reconstruction of Physical Objects
3/31-4/17 - GP/CEO for Stiffness Reconstruction using results from Geometry Reconstruction
4/17 - Functional GP/CEO for Stiffness Utilizing Geometry Results
4/17-4/28 - Conversion of Code to C++
4/17-4/28 - Stiffness Reconstruction and Geometry Reconstruction in Tandem
4/28 Functional Full Tissue Reconstruction with simultaneous Stiffness and Geometry GP/CEO in Matlab/C++
4/28-5/5 - Characterization of Simultaneous vs Sequential full tissue reconstruction
4/28-5/9 - Final Presentation Preparation, Project Documentation
5/9 Final Presentation, Fully Documented Project

Reading List:

1. C. E. Rasmussen & C. K. I. Williams, Gaussian Processes for Machine Learning, the MIT Press, 2006, ISBN 026218253X. c 2006 Massachusetts Institute of Technology.
2. Ebden, Mark. *Gaussian Process for Regression: A Quick Introduction*. N.p., Aug. 2008. Web.
3. Neal, R.M.: Regression and classification using Gaussian process priors (with discussion). In Bernardo, J.M., et al., eds.: Bayesian statistics 6. Oxford University Press (1998) 475–501
4. Williams, C.K.I.: Prediction with Gaussian processes: From linear regression to linear prediction and beyond. In Jordan, M.I., ed.: Learning in Graphical Models. Kluwer Academic (1998) 599–621
5. Kroese, D. "The Cross-Entropy Method." *A Unified Approach to Combinatorial Optimtimization, Monte-Carlo Simulation and Machine Learning*. By R. Rubinstein. N.p.: n.p., n.d. N. pag. Print.