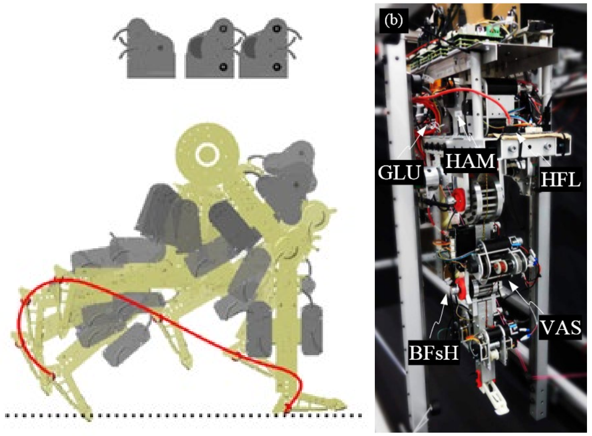
COMPUTATIONAL MODELING IN SUPPORT OF NASA'S HUMAN RESEARCH PROGRAM

Alexander Schepelmann, Ph.D. | NASA GRC Machine Learning Forum | 2019-07-29

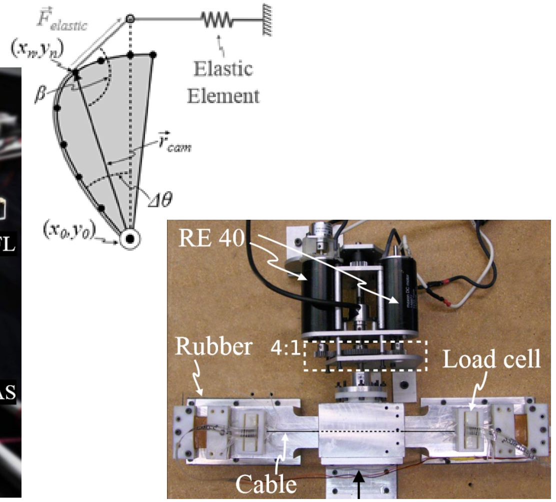
ZIN Technologies, Inc.

ABOUT ME

CWRU: CWRU Cutter autonomous lawnmower.

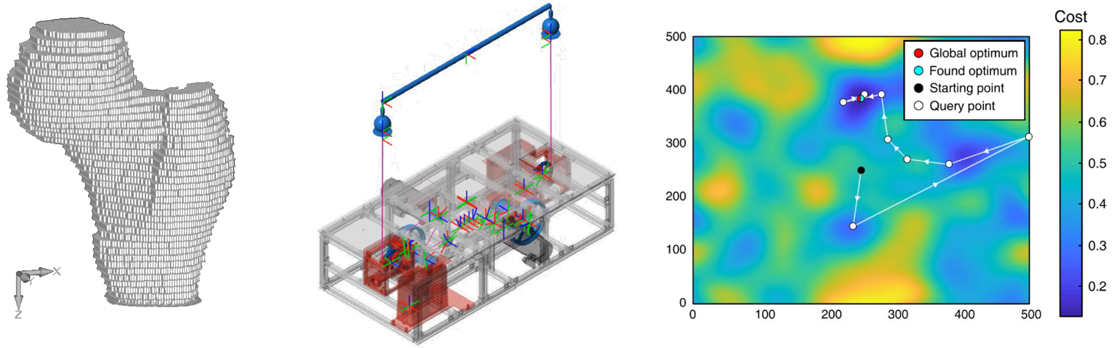


CMU: Robotic Neuromuscular Leg.



CMU: Compact nonlinear SEA springs.

HEBI Robotics: Modular series elastic actuators (SEAs).



ZIN Technologies: Robotics and computational modeling for human spaceflight.

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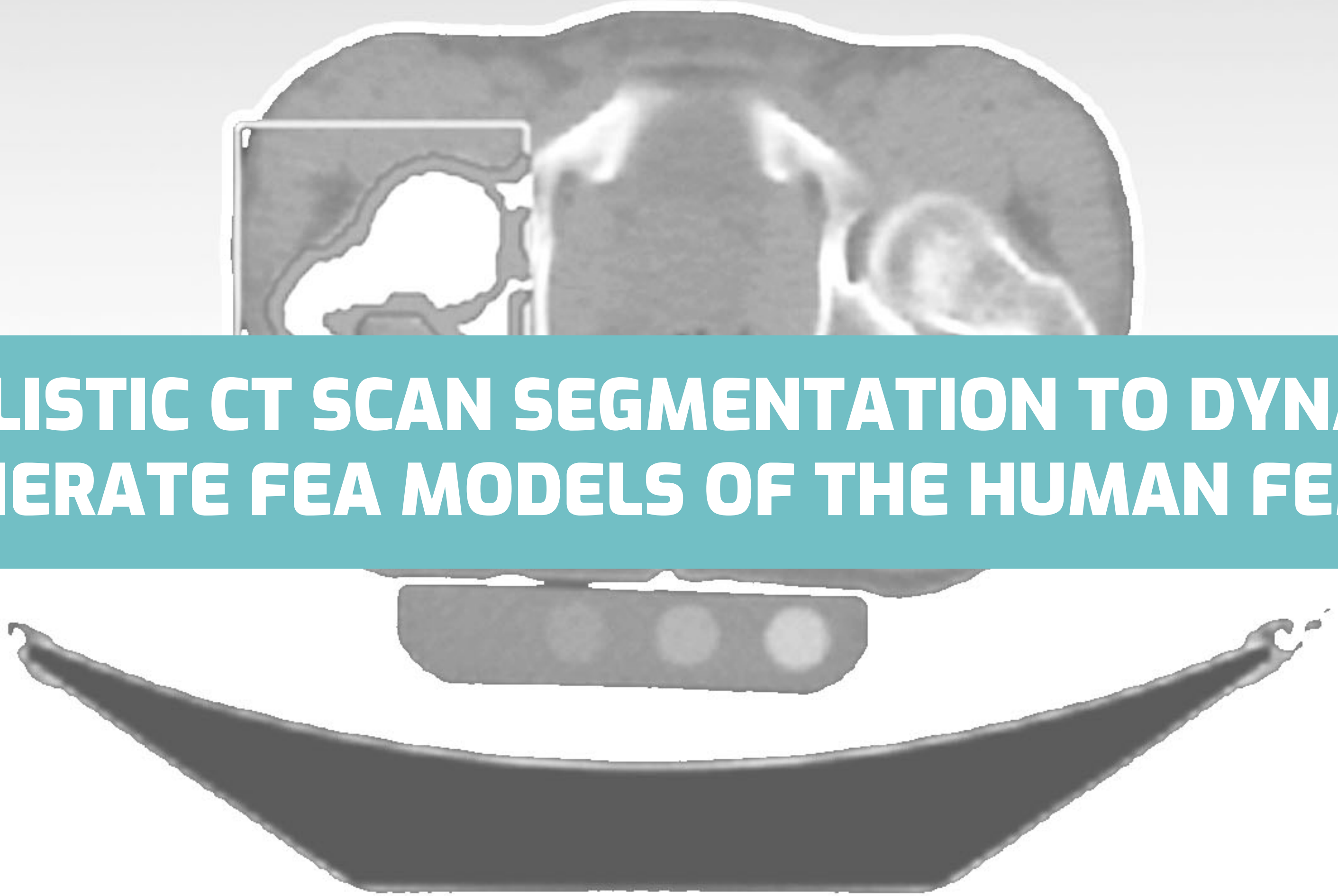
PROBABILISTIC CT SCAN SEGMENTATION TO DYNAMICALLY GENERATE FEA MODELS OF THE HUMAN FEMUR

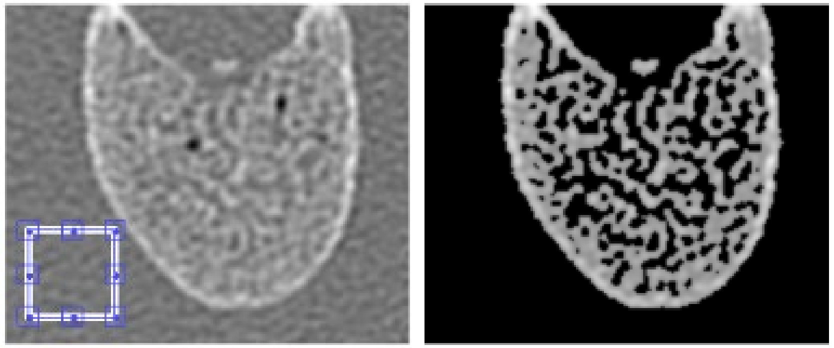


LONG-DURATION SPACEFLIGHT IS DETRIMENTAL TO BONE HEALTH

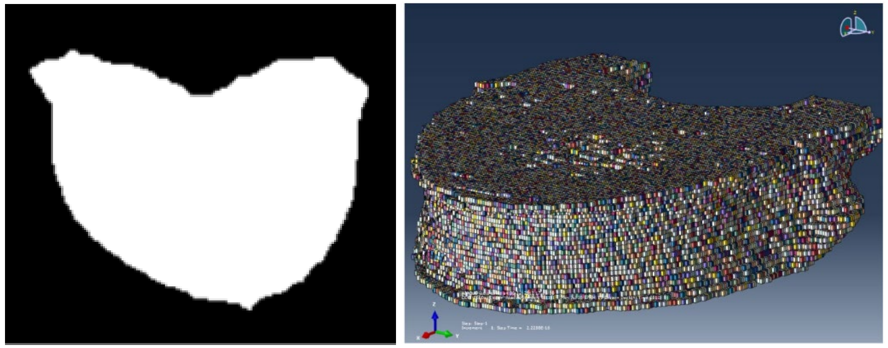
- 0.4-2.7% monthly volumetric bone mineral density (vBMD) loss.
- Resistive exercise counters effects of microgravity.
- Required frequency and duration of exercise is unclear.

Hybrid Ultimate Lifting Kit (HULK) exercise device.

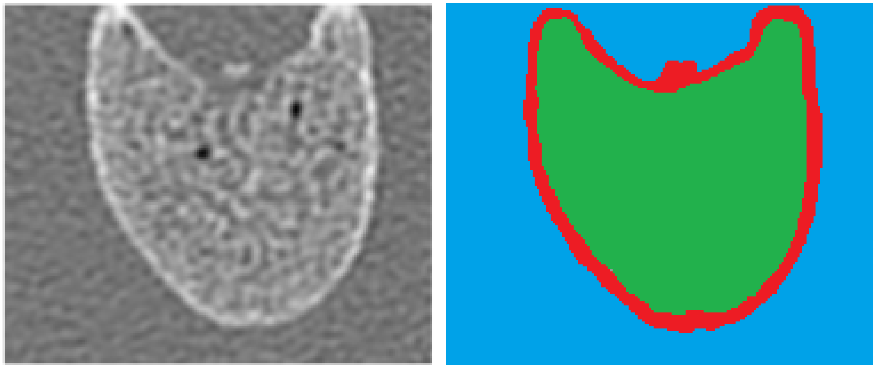
FEA MODELS CAN BE USED TO CALCULATE BMD MAINTENANCE LOADS



Manual calibration results:
Produces noisy output that requires additional, manual post-processing.



Voxel initialization based solely on pixel intensity:
Produces heterogeneous mixture of elements that may be poorly initialized with zero stiffness.



Desired scan processing output (hand-labeled):
Segmented bone cross-section that distinguishes between cortical, trabecular, and non-bone containing regions.

PROBABILISTIC CLASSIFICATION: BETTER, AUTOMATIC SEGMENTATION

"Probability that feature X equals x_i given that sample Y belongs to group y_j"

"Probability that sample Y belongs to group y_j"

$$P(Y = y_j | X = x_i) = \frac{P(X = x_i | Y = y_j) P(Y = y_j)}{P(X = x_i)}$$

"Probability that sample Y belongs to group y_j given that feature X equals x_i"

"Probability that feature X equals x_i"

Bayes' theorem.

FEATURE CLASSIFICATION ONLY RELIES ON RELATIVE LIKELIHOOD

$$P(Y|X) \propto P(X|Y)P(Y)$$

Bayes' theorem numerator:
The conditional probability is proportional to the joint probability model.

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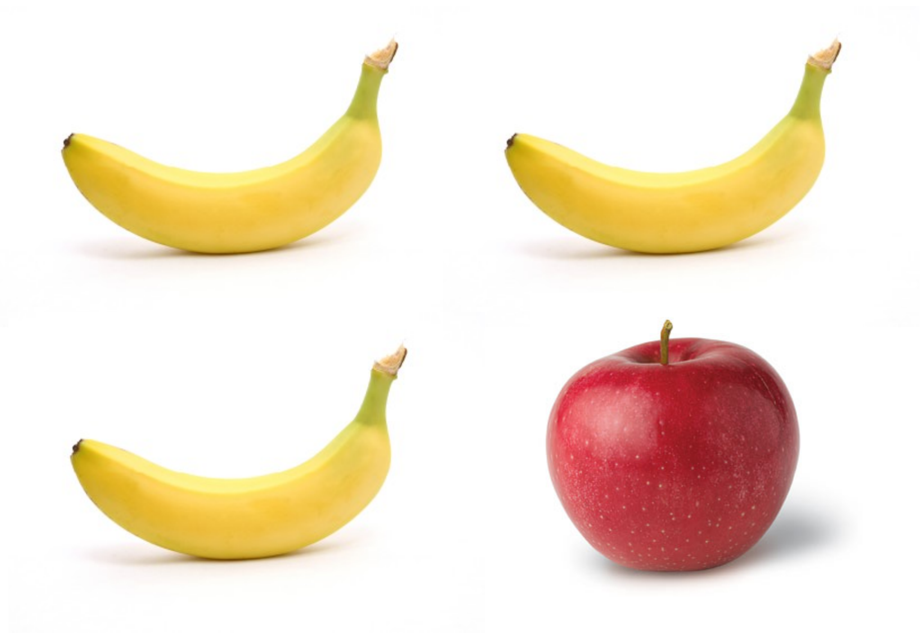
GNB CLASSIFICATION EXAMPLE: CLASSIFYING FRUIT USING ONE FEATURE

$$P(Y = 🍎 | X = 🟨) \propto P(X = 🟨 | Y = 🍎) P(Y = 🍎)$$

$$\propto 0 * 0.25 = 0$$

$$P(Y = 🍌 | X = 🟨) \propto P(X = 🟨 | Y = 🍌) P(Y = 🍌)$$

$$\propto 1 * 0.75 = 0.75$$



The banana-apple universe, where 75% of all fruit are bananas.

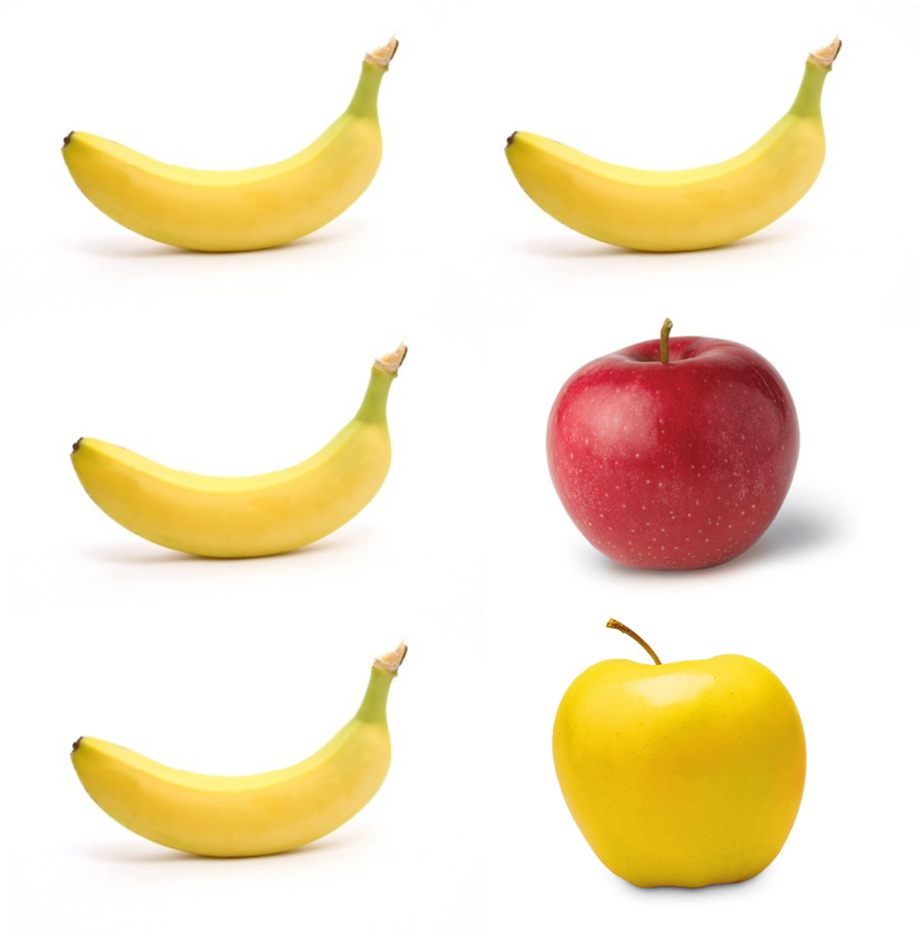
GNB EXAMPLE: CLASSIFYING APPLES WITH INSUFFICIENT FEATURES

$$P(Y = \text{🍎} \mid X = \text{🟨}) \propto P(X = \text{🟨} \mid Y = \text{🍎})P(Y = \text{🍎})$$

$$\propto 0.2 * 0.33 = 0.07$$

$$P(Y = \text{🍌} \mid X = \text{🟨}) \propto P(X = \text{🟨} \mid Y = \text{🍌})P(Y = \text{🍌})$$

$$\propto 0.8 * 0.66 = 0.53$$



The banana-apple universe, where 66% of all fruit are bananas and yellow apples exist.

MORE FEATURES WITH NAÏVE ASSUMPTIONS IMPROVE ACCURACY

$$P(Y|X_1, ..., X_n) \propto P(X_1, ..., X_n|Y)P(Y)$$

Assuming statistically independent features: $$P(X_1, ..., X_n|Y) = \prod_{i=1}^{n} P(X_i|Y)$$

$$P(Y|X_1, ..., X_n) \propto P(Y) \prod_{i=1}^{n} P(X_i|Y)$$

NAÏVE BAYES = INDEPENDENT FEATURE MODEL + DECISION RULE

Given: $X^{new} = < X_1, \ldots, X_n >$

$$\hat{y} = \underset{j \in \{1,\ldots,J\}}{\operatorname{argmax}} \propto P(Y = y_j) \prod_{i=1}^{n} P(X_i^{new} | Y = y_j)$$

Naïve Bayes classifier using the maximum a posteriori decision rule:
Based on the features, it is most probable that the item being classified belongs to group.

GNB EXAMPLE: CLASSIFYING APPLES WITH MULTIPLE FEATURES

$$P(Y = \text{banana} | X = \text{yellow}, round)$$

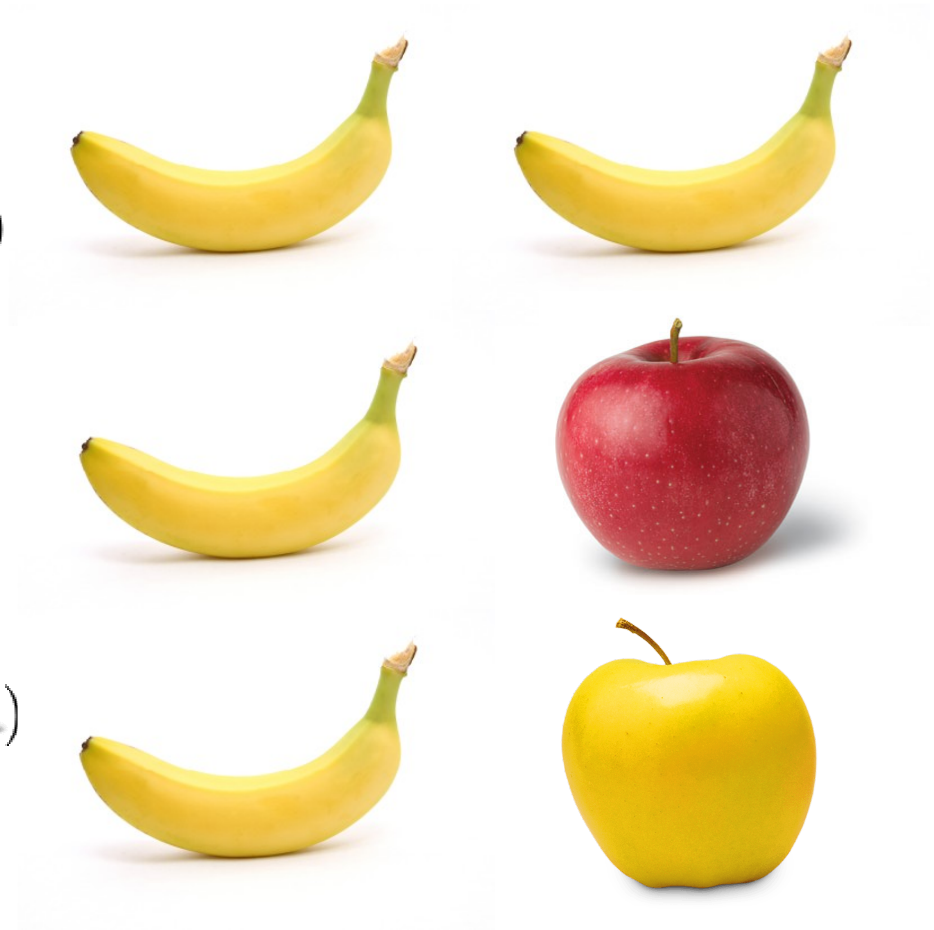
$$\propto P(Y = \text{banana}) * P(X = \text{yellow} | Y = \text{banana}) P(X = round | Y = \text{banana})$$

$$\propto 0.66 * 0.8 * 0 = 0$$

$$P(Y = \text{apple} | X = \text{yellow}, round)$$

$$\propto P(Y = \text{apple}) * P(X = \text{yellow} | Y = \text{apple}) P(X = round | Y = \text{apple})$$

$$\propto 0.33 * 0.2 * 1 = 0.07$$



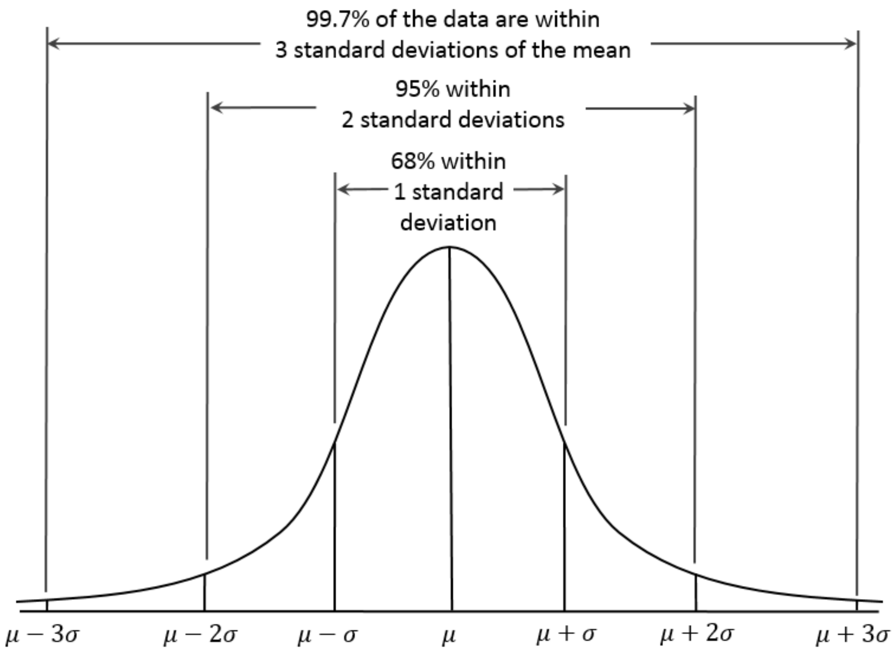
The banana-apple universe, but fruits are described by color <u>and</u> shape.

GAUSSIAN DISTRIBUTION: ESTIMATING SAMPLE FEATURE LIKELIHOOD

$$P(Y = y_j) \prod_{i=1}^{n} P(X_i | Y = y_j)$$

Calculated as (n_{class} / n_{tot})

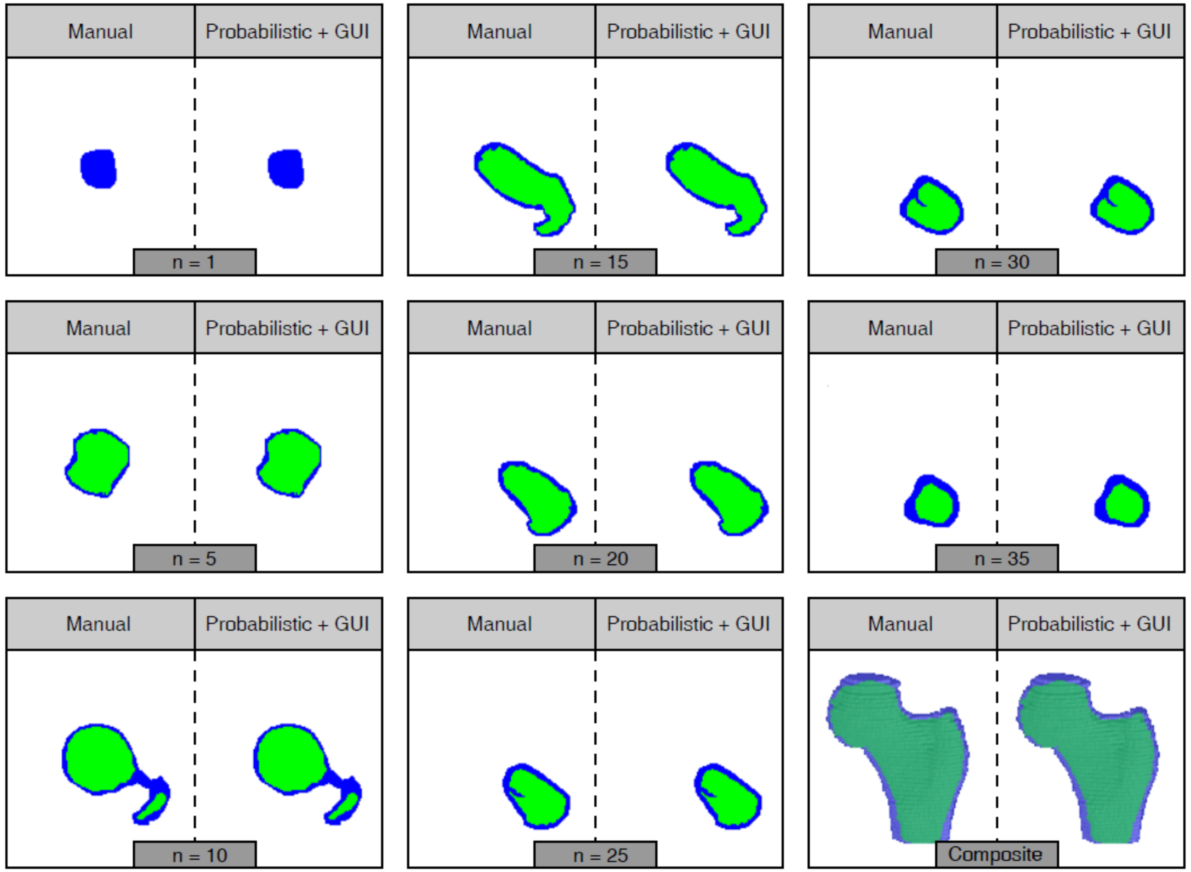
$$P(X = x_i | Y = y_j) = \frac{1}{\sqrt{2\pi\sigma_{y_j}^2}} e^{-(x_i - \mu_{y_j})^2/(2\sigma_{y_j}^2)}$$



The probability density function of a Gaussian distribution.

AUTOMATIC CT IMAGE SEGMENTATION TO BUILD FEA BONE MODELS

- GNB-based approach can generate identical segmentations to manual segmentation.
- Time to segment is much shorter:
    - **10 minutes vs. 8 hours**



Manual vs. Probabilistic + GUI segmentation.

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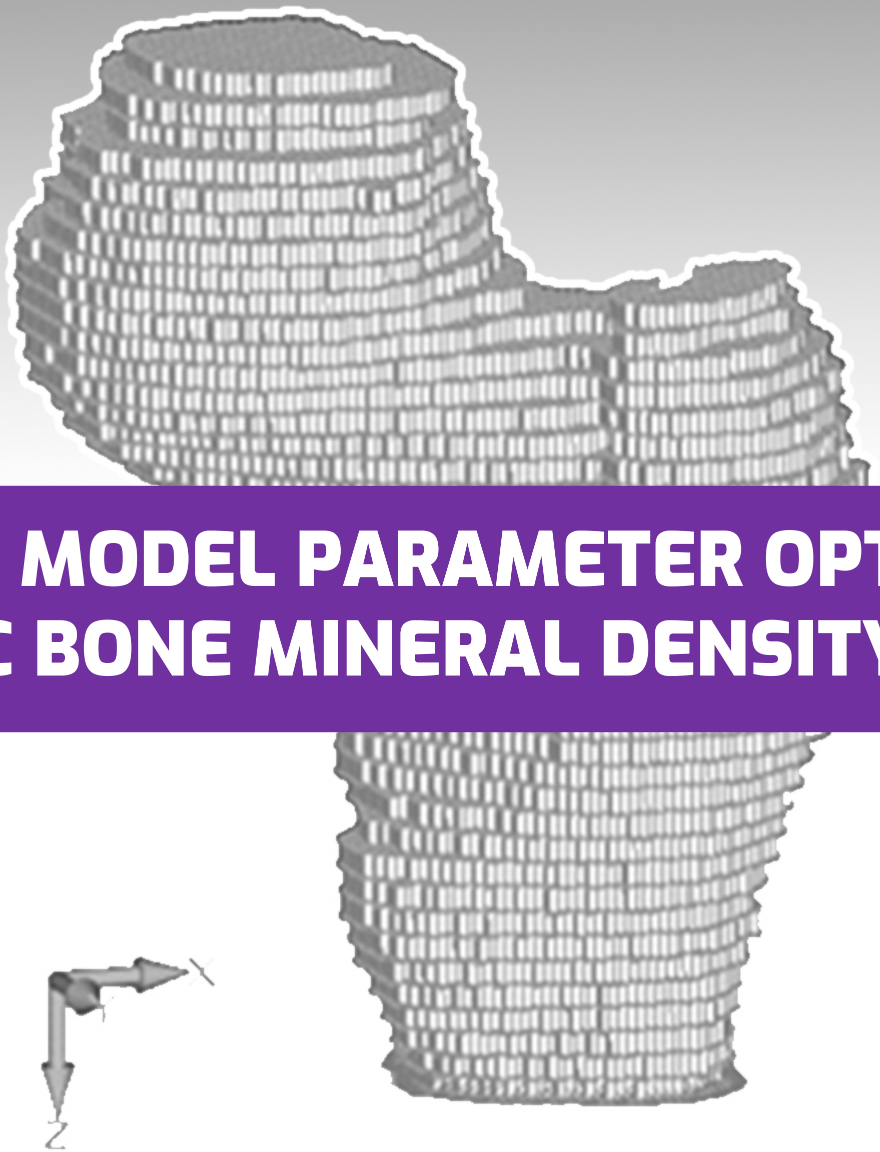
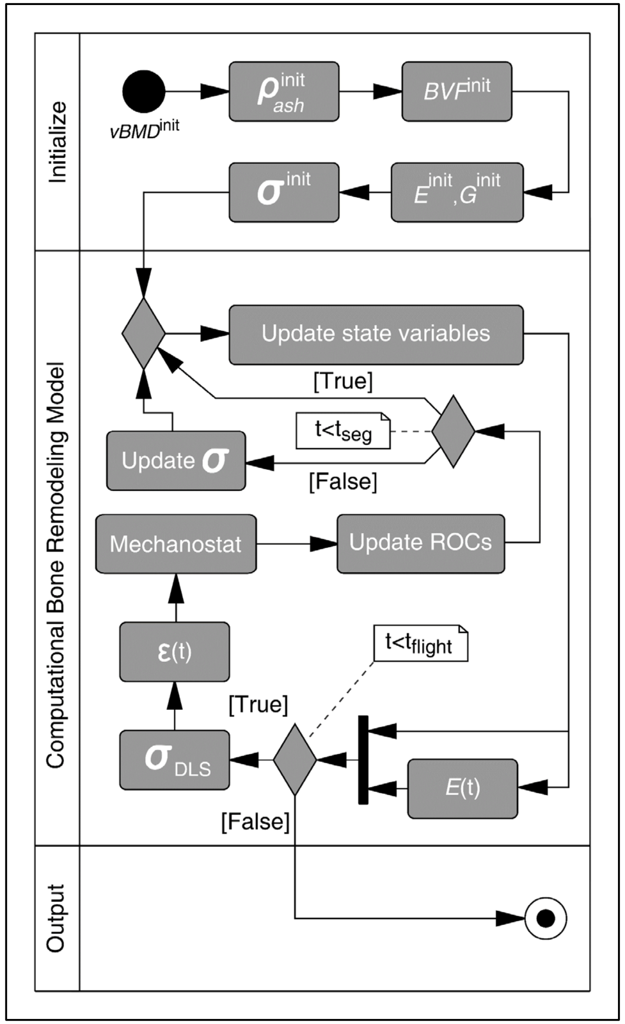


STOCHASTIC MODEL PARAMETER OPTIMIZATION FOR VOLUMETRIC BONE MINERAL DENSITY MAINTENANCE

PREDICTING CHANGES IN VOLUMETRIC BONE MINERAL DENSITY (vBMD)

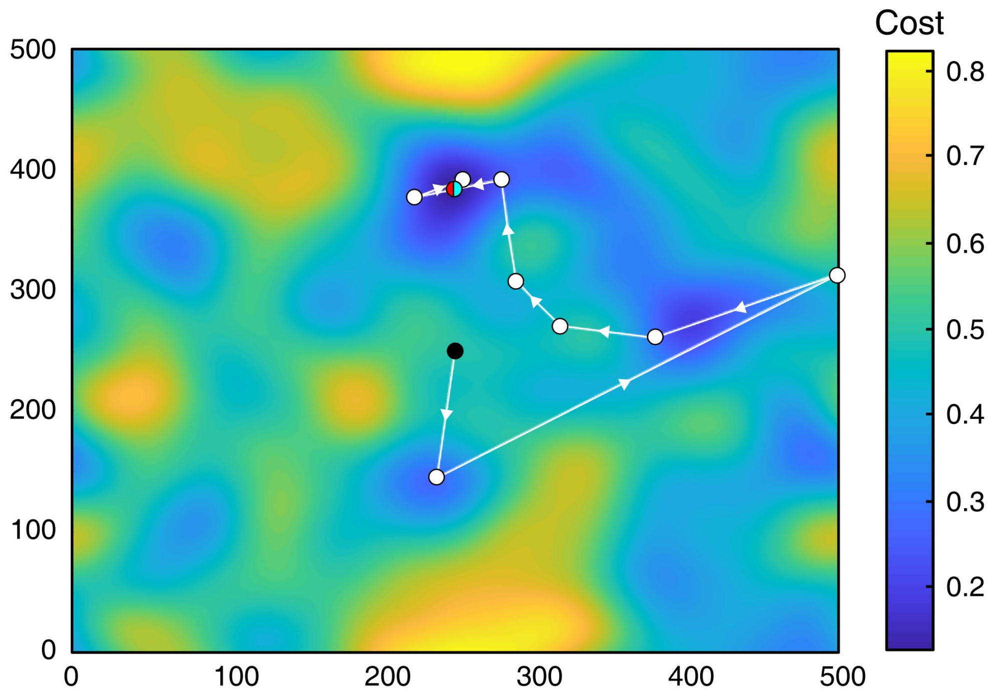
- Generated FE models are used in conjunction with computational bone model.
- Model simulates exercise-induced changes in vBMD.
- Model parameters can be tuned to individual users.
  - Model is highly nonlinear.
  - Number of parameters makes manual tuning difficult.
- Optimization can be used for automatic parameter tuning.



A schematic of the GRC-developed computational bone model.

TUNING MODEL PARAMETERS THROUGH STOCHASTIC OPTIMIZATION

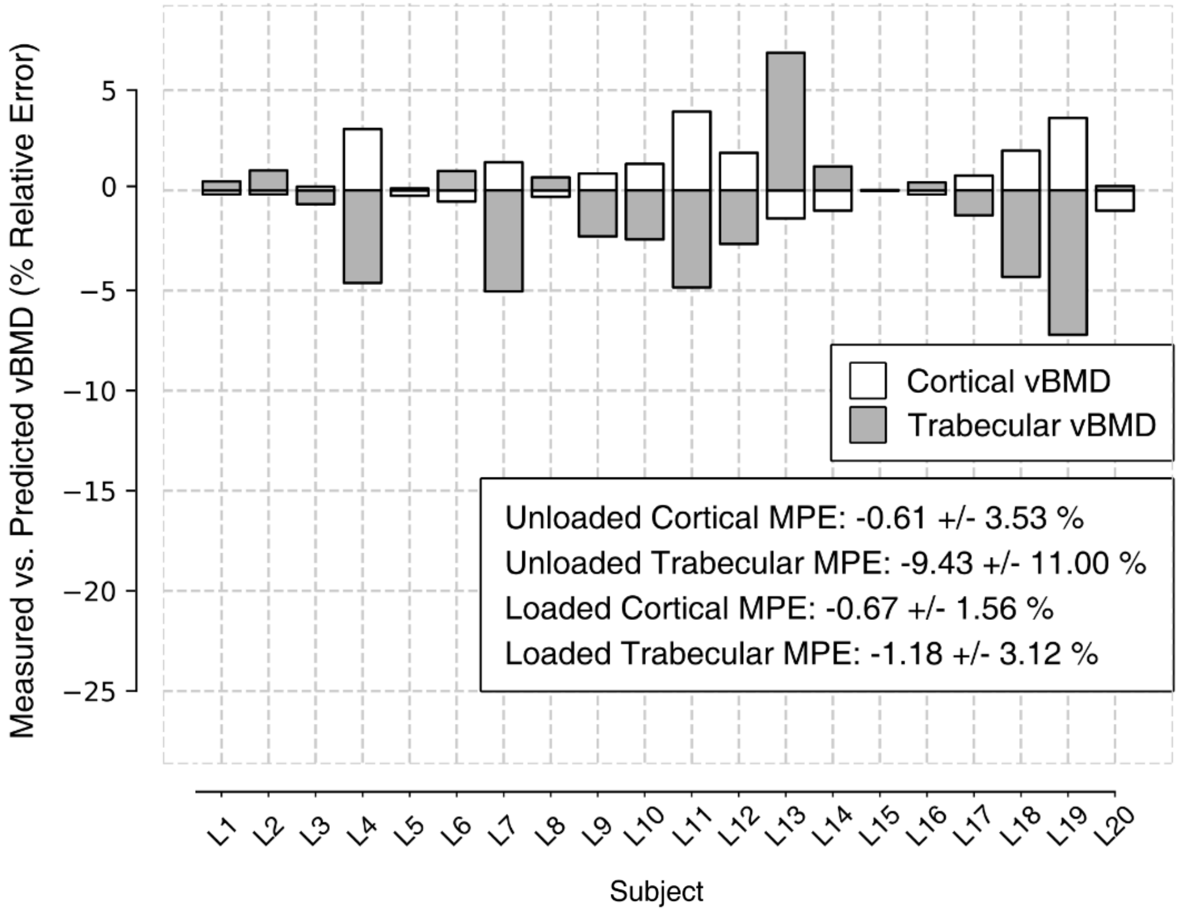
- Model is tuned by minimizing the difference between pre- and post-"flight" vBMDs from an analog study.
- Gradient-based techniques get "stuck" in local minima.
- Stochastic methods may find better minimum.



Example schematic of stochastic optimization process over a 2D cost landscape. Black: Initial value. White: Evaluations. Red: Global optimum. Teal: Found optimum.

COMPUTATIONAL MODEL CAN PREDICT CHANGES IN vBMD

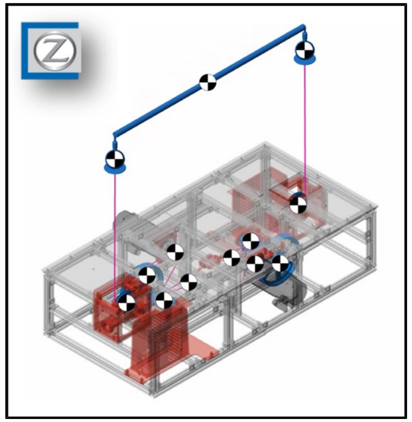
- As a black box, model predicts vBMD changes.
- Some resulting parameters are unrealistic.
- Model fidelity could be improved with:
  - Additional data.
  - Additional constraints.



Relative error between measured and model-predicted changes in vBMD.

MACHINE LEARNING IS CENTRAL TO GRC'S HRP EFFORT

- Probabilistic segmentation and optimization were used to create a predictive model of bone mineral density (vBMD).
- The developed model can accurately predict vBMD and inform required resistive exercise loads for vBMD maintenance.
- This information is used to develop robotic exercise devices.
    - ZIN-developed ATLAS device is currently undergoing testing at JSC.
    - Intended ATLAS goal: use on Gateway and Mars missions.
- Additional information in NASA/TM—2018-219938.




ATLAS: Simulated model (left) and hardware.