Non-Invasive Prediction of Central Hypovolemia

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Disclosures

- Grant Support:
  - Colorado Clinical and Translational Sciences Initiative (NIH)
  - National Space and Biomedical Research Institute (NASA)
  - U of CO, Dept. of Surgery
  - US Army, Department of Defense
- Principal at:
  - 10 Blade, Inc.
  - Flashback Technologies, LLC
- Grants funded or in process with:
  - Sierra Nevada Corporation
  - Impact Instrumentation, Inc.
  - Advanced Circulatory Systems, Inc.
  - Reflectance Medical, Inc.
- Patents pending for:
  - Method for noninvasive blood loss detection
  - Method for predicting hemodynamic decompensation
  - Method for long term learning from continually changing datasets

Technology under discussion is in development and not available for clinical practice

Outline

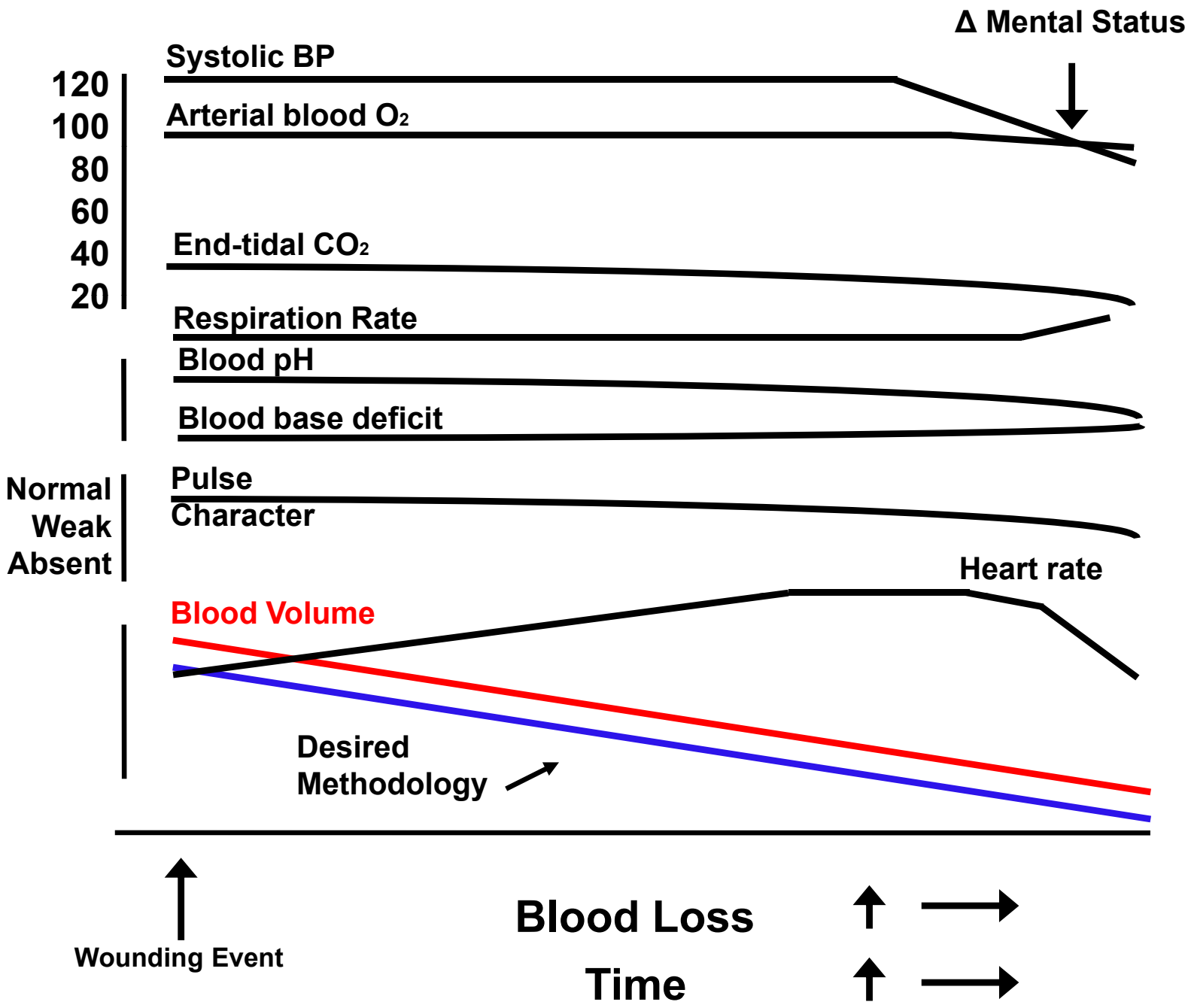
- Surgery and hemorrhage
  - Patients are complex and dynamic
  - Continuous instead of sporadic bedside care
- Robotics
  - Real-time image analysis; high speed data processing
- Machine learning
  - Advanced mathematical modeling; statistical relevance
- Cardiovascular physiology
  - Large amounts of complex, high-fidelity data
  - Human LBNP model of acute blood loss
- Discovered
  - Several previously hidden hemodynamic relationships
  - New method to analyze real-time physiological data

Hemorrhage

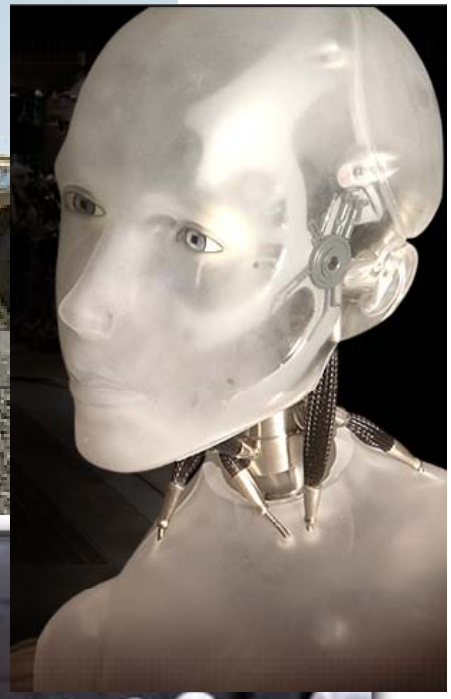
- Accounts for 40% of all trauma deaths[1]
  - most frequent cause of preventable death after injury
- Tissue trauma causes hemorrhage, initiates coagulation
- Shock (hypoperfusion)
  - Primary driver of early, post-injury coagulopathy[2]
  - Dose dependent correlation between severity of tissue hypoperfusion and admission coagulopathy[3,4]
- Diagnosis and treatment
  - Identify bleeding early <u>and</u> prevent hypotension
  - Correct coagulopathy <u>and</u> stop the bleeding

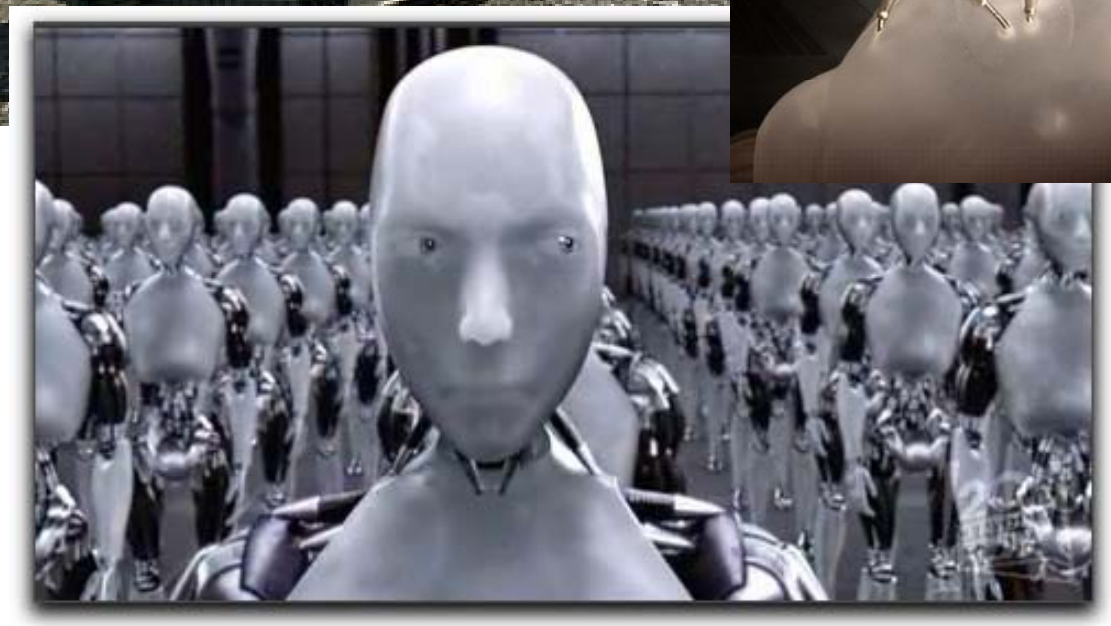
1. Sauaia A, Moore FA, Moore EE, et al. *J Trauma*. 1995;38:185
2. Hess J, Brohi K, Dutton R, et al. *J Trauma*. 2008;65:748
3. Brohi K, Cohen MJ, Ganter MT, et al. Ann Surg. 2007;245:812
4. Niles SE, McLaughlin DF, Perkins JG, et al. J Trauma. 2008;64:1459

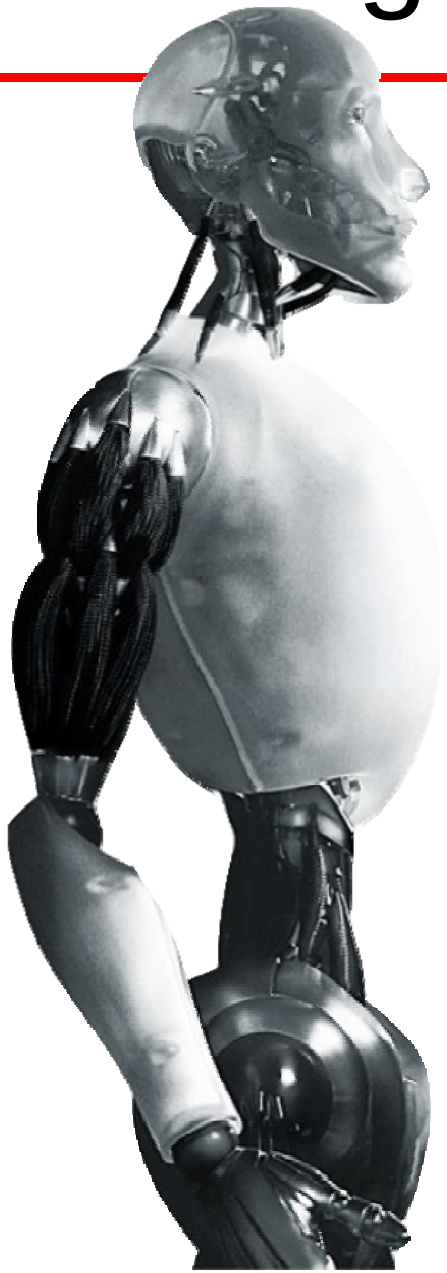
Humans Cannot Detect Early Signs Hemorrhage



Robots and Machine Learning







Robots

- Autonomous robot navigation depends on
  - Identification of navigable terrain
  - Stereo and color imaging reconstruction
    - Provide info about ground plane features in the near field
    - Need far field planning (> 50 meters)
- Greg Grudic and Jane Mulligan
  - University of Colorado
  - Machine learning methods
    - Near-to-far learning
    - Near field terrain appearance and stereo readings used to train models able to predict far field terrain

Machine Learning

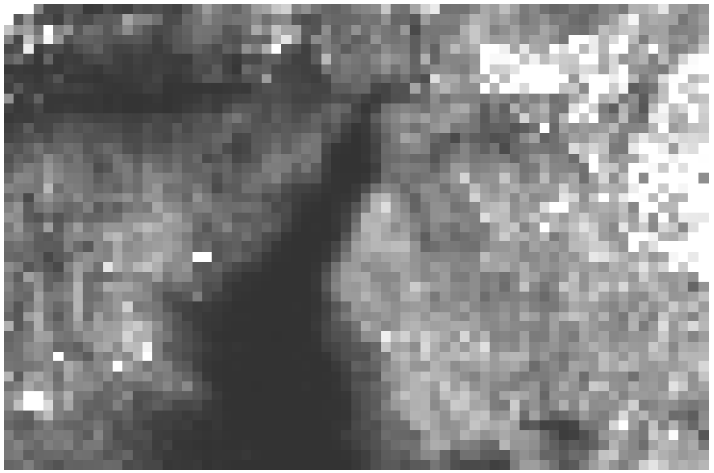
- Subfield of artificial intelligence
  - Design and development of algorithms and techniques that allow computers to “learn”
  - Extract information from massive data sets using computational and statistical methods
    - Extracts relevant sensor information predictive of a condition
    - Builds predictive models of the condition
    - Determines the accuracy of the models
    - No human intervention is needed!
  - Exposes hidden relationships in the data, faster and more accurately than any human

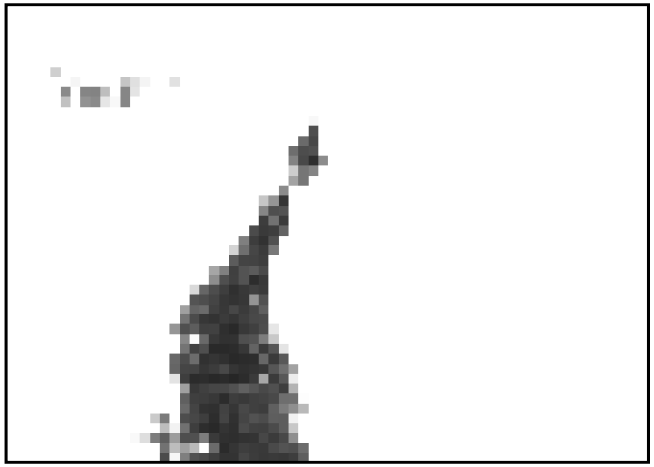
Robots

- LAGR (Learning applied to ground robots)
  - DARPA program
  - Image-based navigation system
  - Each camera (640 x 480 pixels) = 307,200 pixels/image
  - RGB (multiply x 3) = 921,600 pixels/image
  - 30 frames/sec = 27,648,000 pixels/image-sec
  - 4 cameras (multiply x 4) = 110,592,000 pixels/image-sec
- Robot captures and processes > 100M data points/second

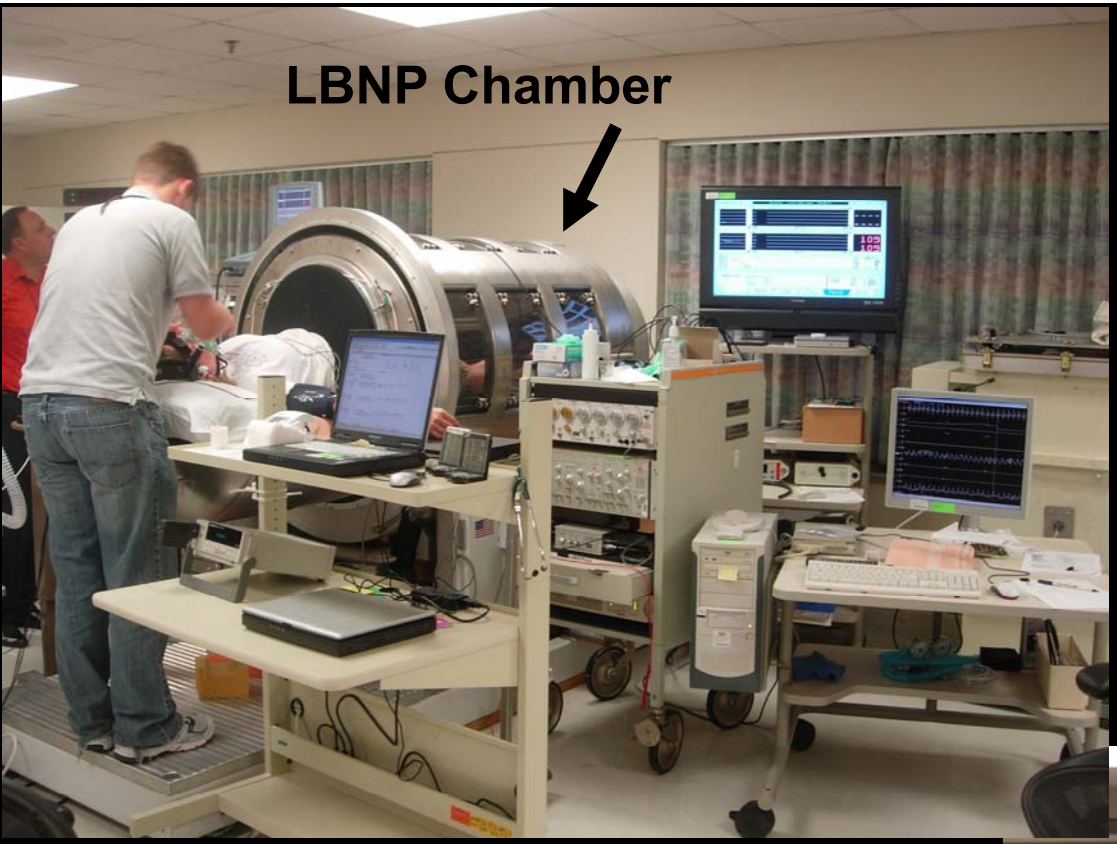
Robots

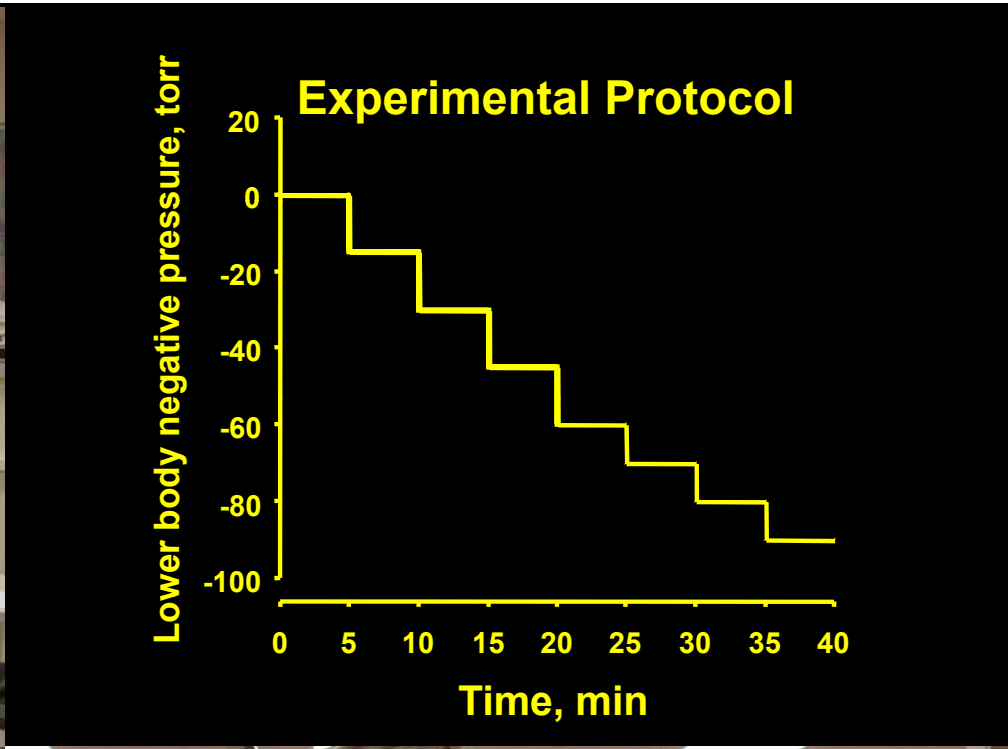
- LAGR uses machine learning techniques
  - Learns sets of fast, efficient density models in real-time, in unknown, unstructured terrains
  - Navigation system chooses whether to:
    - Apply current models
    - Discard inappropriate models
    - Acquire new models…on its own
      - Without human intervention

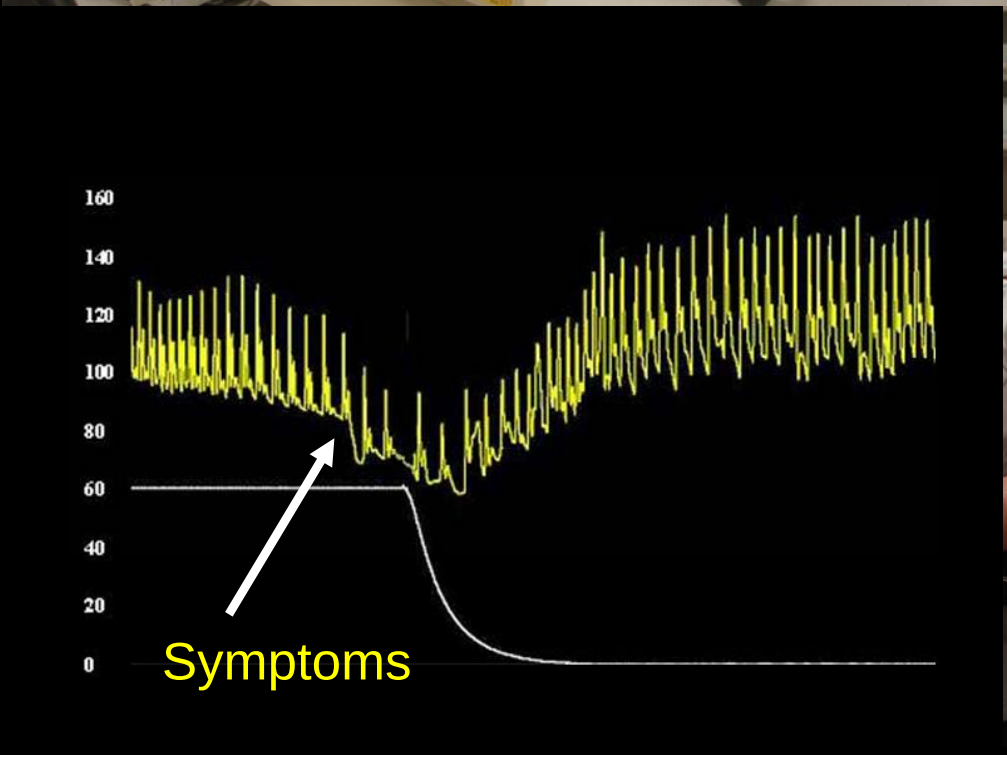




Could these same methods be used to ***learn*** and ***build*** sets of models, able to ***predict*** changes in human physiology in ***real-time***?


LBNP Chamber


Experimental Protocol
Lower body negative pressure, torr
20
0
-20
-40
-60
-80
-100
0
5
10
15
20
25
30
35
40
Time, min

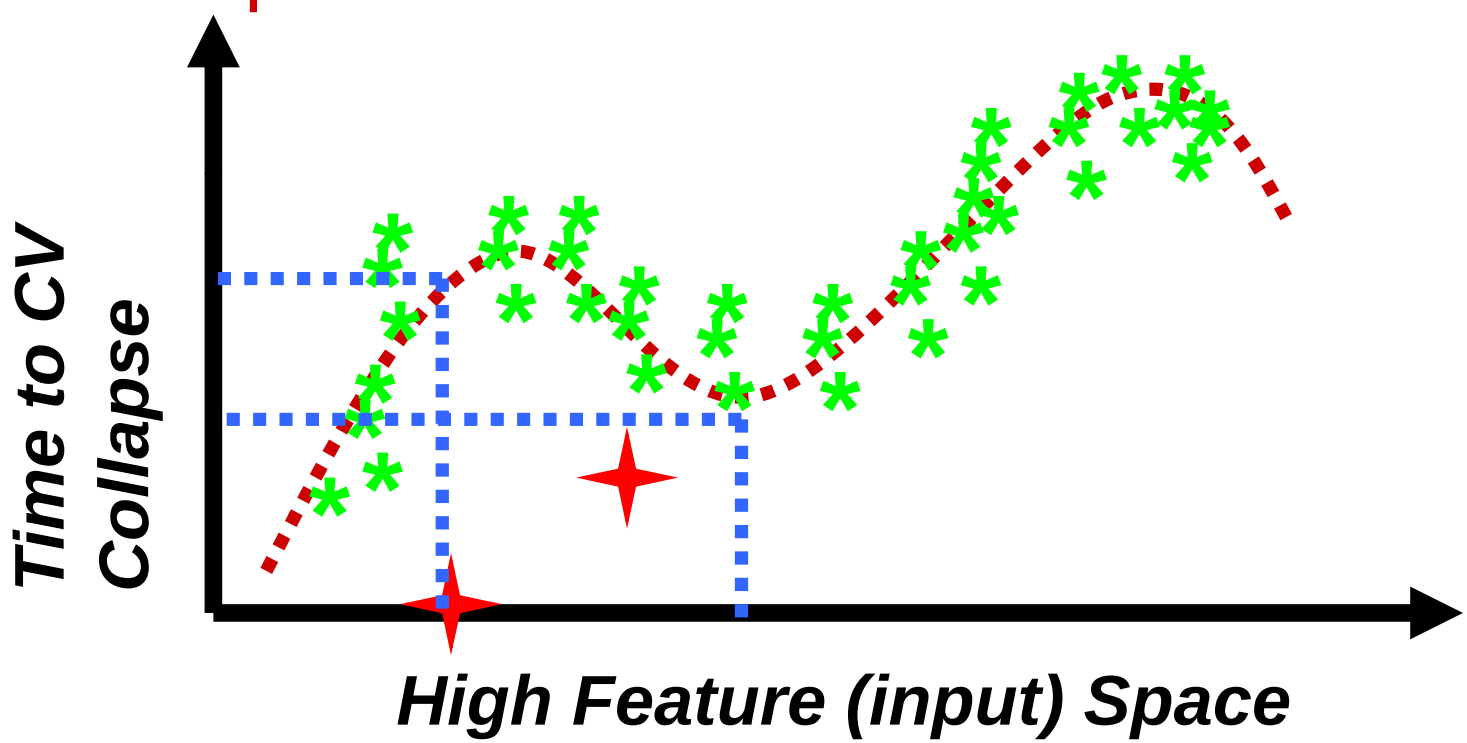

160
140
120
100
80
60
40
20
0
Symptoms

Learning Regression Models

- Collect Training data, map into feature space

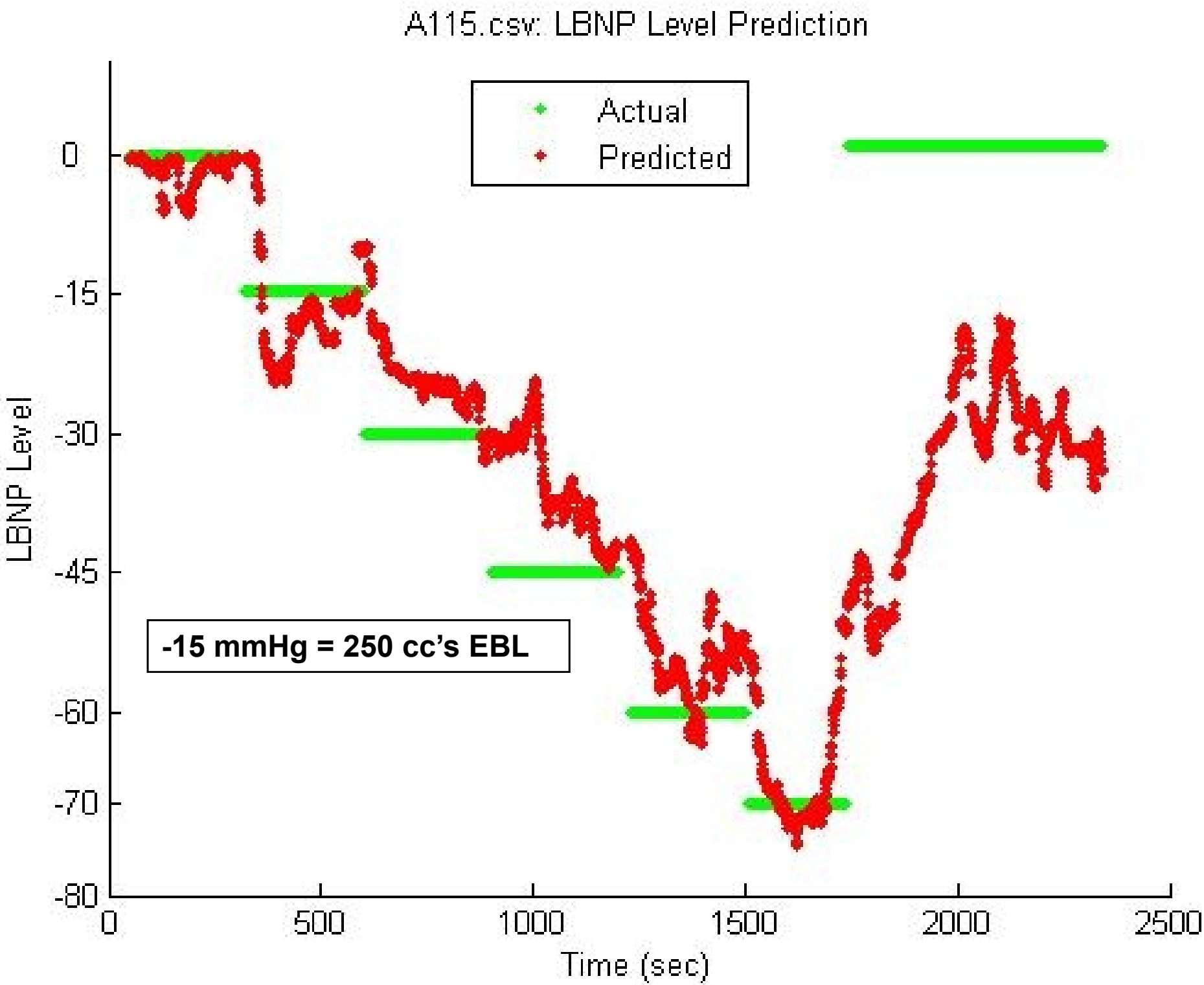
$$f(\mathbf{x}) = \sum_{i=1}^{d} \beta_i x_i + \beta_0 \qquad f(\mathbf{x}) = \beta_1 x_1 x_2 + \beta_2 x_1^2 x_2^3 x_{56} x_{106} + \cdots$$

- Build Model: y = Model (feature space)
- Make a prediction



Model Development

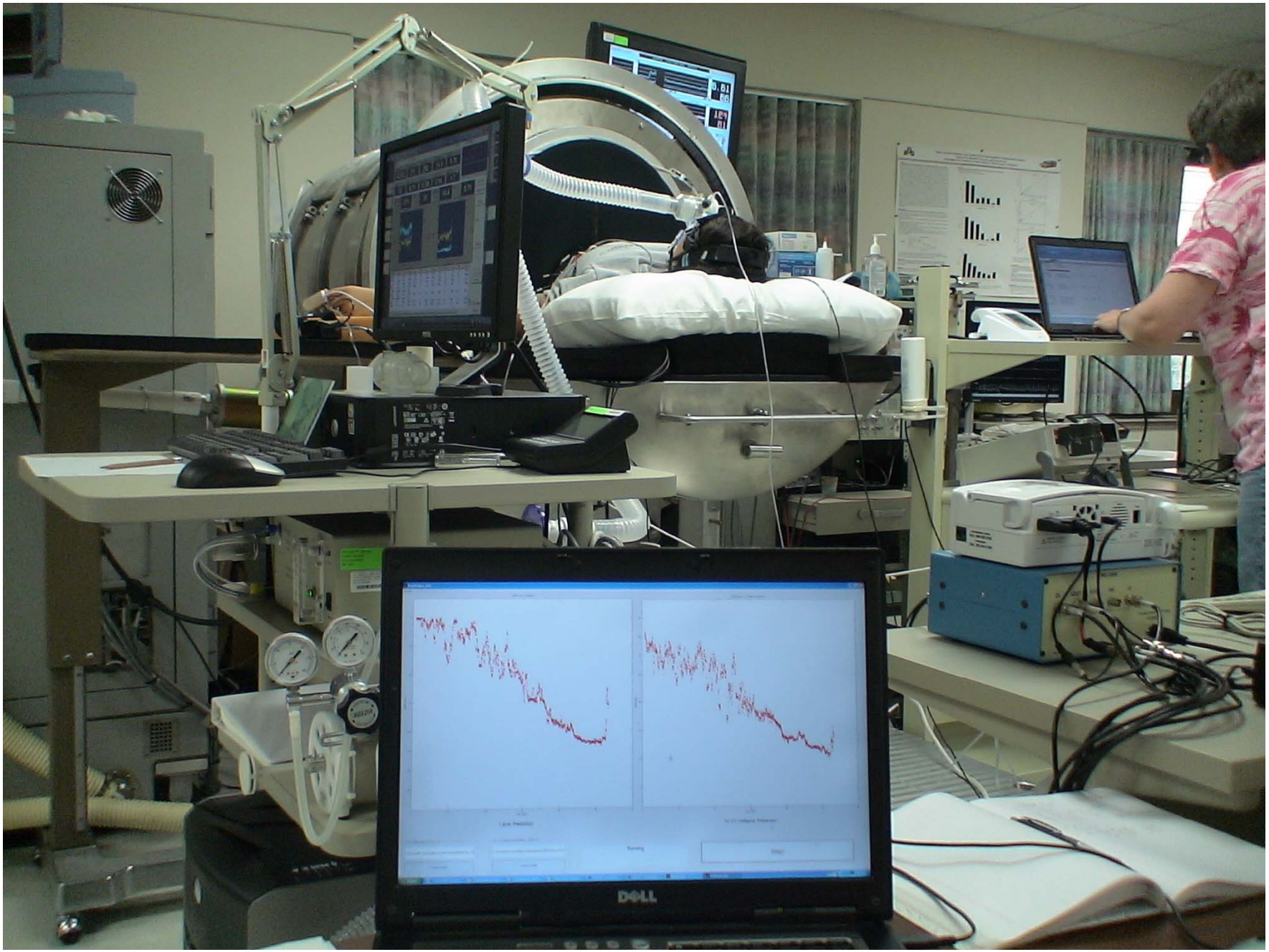
- Used archived LBNP data from 28 experiments
  - Built models using 27 subjects, tested on 28th
  - Repeated process 28 times
- First model:
  - Used standard, non-invasive vital sign data
  - Initial sample size = 64 beats
  - New prediction made w/ each subsequent beat
  - Compared Actual with Predicted LBNP


A115.csv: LBNP Level Prediction
Actual
Predicted
-15 mmHg = 250 cc's EBL
LBNP Level
0
-15
-30
-45
-60
-70
-80
0
500
1000
1500
2000
2500
Time (sec)

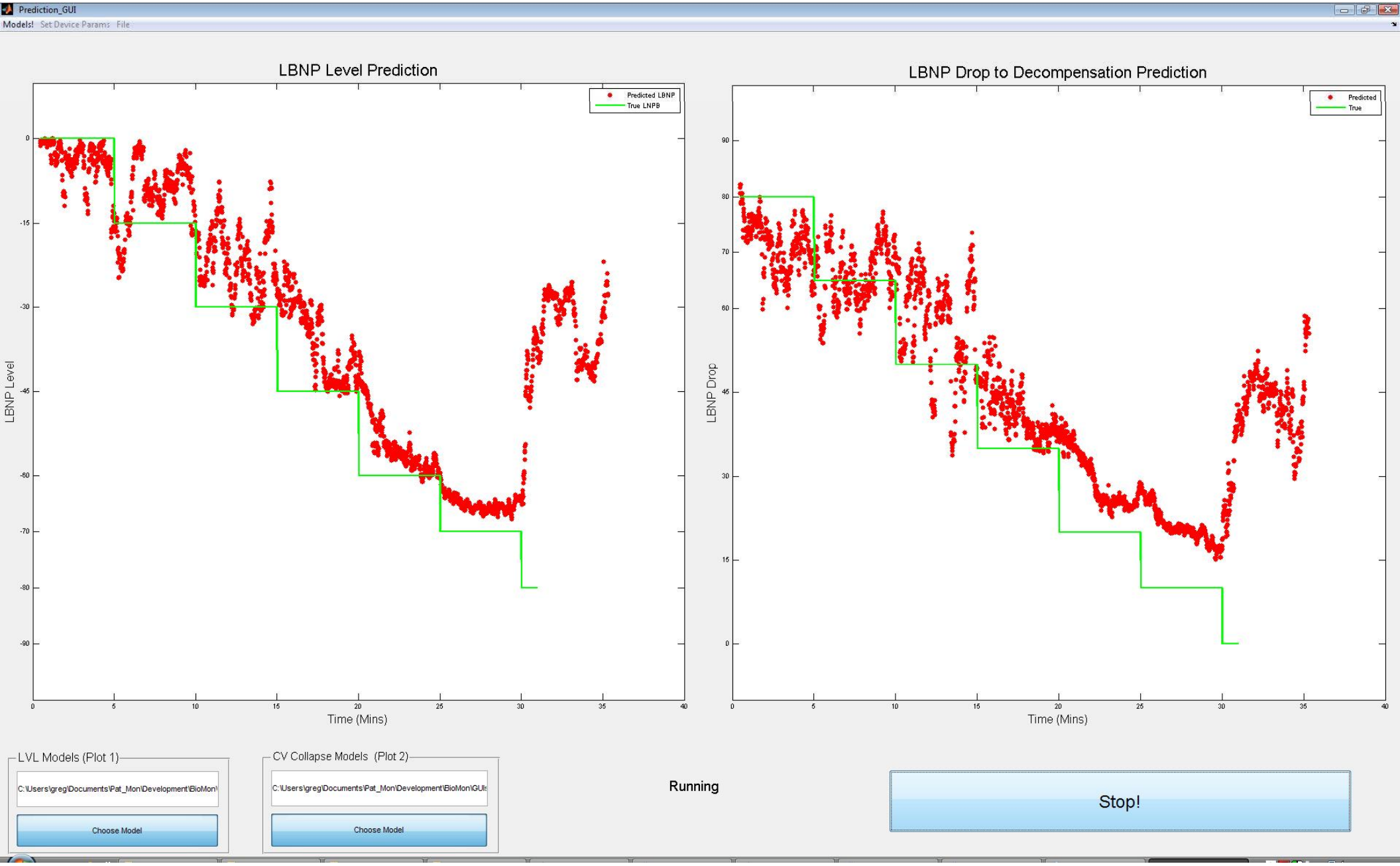
Results

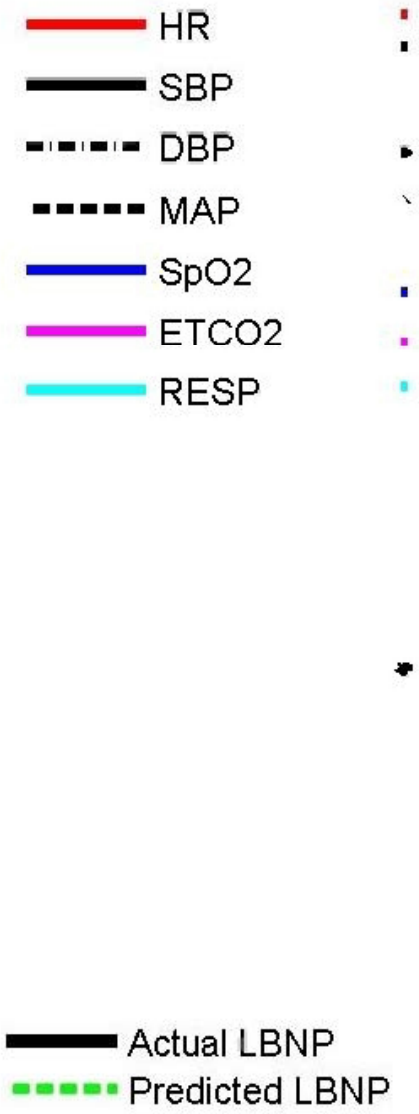
- First model accuracy estimates:
  - Results are an average of the 28 experiments
  - Correlation between Predicted and Actual LBNP was 0.96
  - Correlation between Predicted LBNP level at which subjects decompensated versus Actual level was 0.89

Real-time Testing



Real-time Testing




HR
SBP
DBP
MAP
SpO2
ETCO2
RESP
Actual LBNP
Predicted LBNP

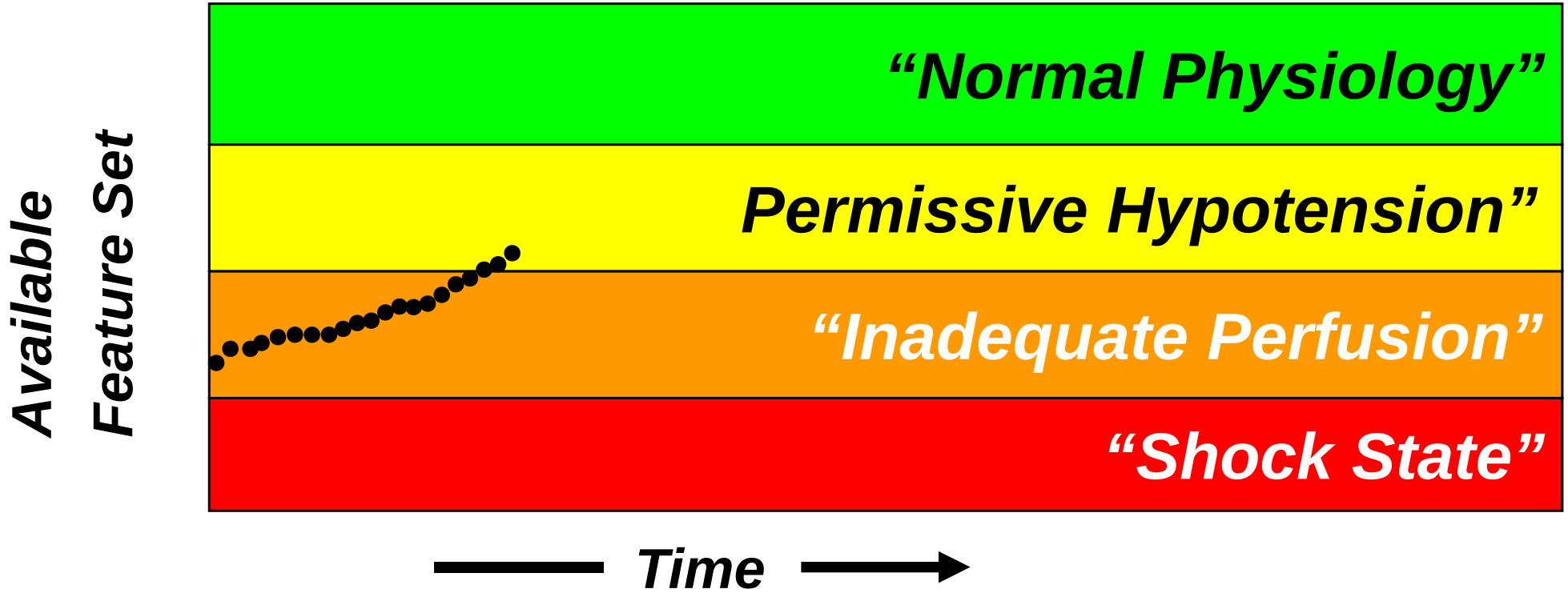
Next Steps

- Baboon studies planned
  - Validate and improve accuracy of the algorithm
- Reduce latency
- Shrink form factor
  - Algorithm is lightweight, fast
  - What is an optimal feature set? What platform?
- M.L. Algorithms will:
  - Automatically determine sensor types available
  - Only make predictions when confident with data sensed
    - Filter out noise; chose from signals available
- Automatically determine optimal feature sets
  - may be dependent on setting
    - Battlefield vs. pre-hospital vs. In-hospital: ED, OR, ICU, ward

Next Steps

- Investigate other clinical scenarios
  - Fluid resuscitation; end points of resuscitation
  - TBI: CBF, ICP and CPP relationships
  - Optimal ventilator management
  - Arrhythmia analysis
  - Depth of anesthesia, etc.
- Collection and analysis of ***complex data sets*** will enable us to uncover hidden physiological relationships that are predictive of a patient's clinical course

Machine learning techniques will fundamentally change resuscitative care from a process filled with ***guesswork***, to *a* ***predictive*** *and eventually an* ***automated*** process



Summary

- Additive technologies leading to emergence of artificial intelligence applications in medicine
  - Smart systems that **perceive** their environment (the patient) *and* **take actions** (autonomously), based on maximal (**predicted**) chances for success

Collaborators

- University of Colorado
  - Greg Grudic, PhD
  - Jane Mulligan, PhD
  - Abhishek Jaiantilal, MS
  - Michael Otte, MS
- US Army Institute of Surgical Research
  - Victor Convertino, PhD
  - Kathy Ryan, PhD
  - Caroline Rickards, PhD
  - Steven Glorsky, MD