Medical Knowledge Engineering Session

Are Standard Vital Signs Useful in Early Trauma Casualty Care? A New Look at an Old Problem	Dr. Jaques Reifman BIC/BHSAI/TATRC/MRMC
Visensia – A System for Early Warning of Clinical Deterioration	Mr. Wayne Nethercutt OBS Medical
A Platform for Testing and Comparing of Real-Time Decision-Support Algorithms in Mobile Environments	Mr. Maxim Khitrov BIC/BHSAI/TATRC/MRMC
A Vital Sign Based Decision Support System for Evaluating Post-Surgical Hospital Patients	Dr. Neal Sanders Vanderbilt University

Are Standard Vital Signs Useful in Early Trauma Casualty Care?

A New Look at an Old Problem

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opinions, interpretations, conclusions, and recommendations are those of the authors and are not necessarily endorsed by the U.S. Army or the U.S. Department of Defense

BIC

TATRC

Primary Goal

Develop fieldable decision-support algorithms for triage and diagnosis of trauma casualties

Requirements:

- Handle challenges of real-world data
  - Imperfect measurements and often missing data
  - Confounding effects and imperfect knowledge of outcomes
- Decision support applicable to each and every individual casualty

First Step: Develop decision-support algorithms through retrospective analysis of prehospital standard vital signs, while addressing requirements

- establish a benchmark for basic vital signs -

Strategy to Establish a Benchmark

- Systematic retrospective analysis of vital-sign data
  - Step-by-step, evidence-based analysis
  - Numerous sensitivity analyses
- Explicitly identify and address potential sources of error
  - Potential for bias
- Parsimonious approach
  - All other things being equal, the simplest solutions are the best

Prehospital Trauma Data for Retrospective Analysis

- 783 patients (~25 min of transport time/patient)
- High-frequency vital-sign waveforms (3 waveforms)
  - ECG, SpO2, Respiratory
- Low-frequency vital-sign time series (9 variables)

  Derived variables
  - ECG heart rate
  - SpO2 heart rate
  - SaO2 arterial O2 saturation
  - Respiratory rate

  Measured variables
  - NIBP (systolic, diastolic, MAP)
  - NIBP heart rate
  - End tidal CO2
- Discrete patient attribute data (100 variables)
  - Demographics, injury description, prehospital interventions, etc.

Vital signs used in decision-support algorithms

Propaq

HR
RR
SaO2
SBP
DBP

Decision Support for Hemorrhage Discrimination

Outcomes: Patients were Divided into Two Classes

- Hemorrhage class (hemorrhage, 79 patients)

  Received in-hospital blood (≥1 unit within 24 h upon arrival)

  AND

  Any documented injury associated with major hemorrhage
  - Laceration of solid organs
  - Blood collection in abdomen, thorax, or pelvis
  - Explicit vascular injury and operative repair
  - Limb amputation

- Control class (control, 600 patients)

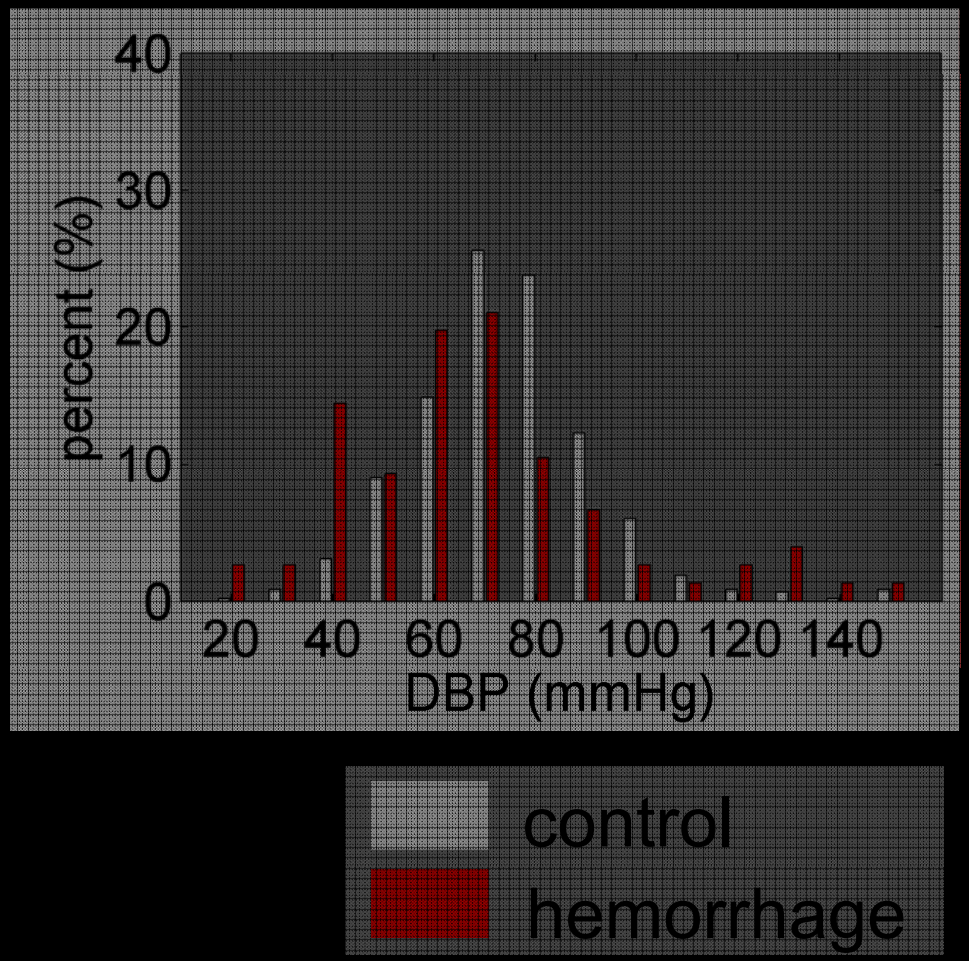
  No in-hospital blood

A Naïve Approach

Use ***first*** vital-sign measurement to identify major hemorrhage cases

Vital Sign (# of Patients)	ROC AUC (95% CI)*
HR (679)	0.58 (0.51-0.66)
RR (637)	0.51 (0.39-0.62)
SaO2 (659)	0.58 (0.46-0.69)
SBP (661)	0.71 (0.64-0.77)
DBP (661)	0.61 (0.53-0.68)

*Area under the receiver operating characteristic curve and 95% confidence interval, computed by the ROCKIT software (U. Chicago)



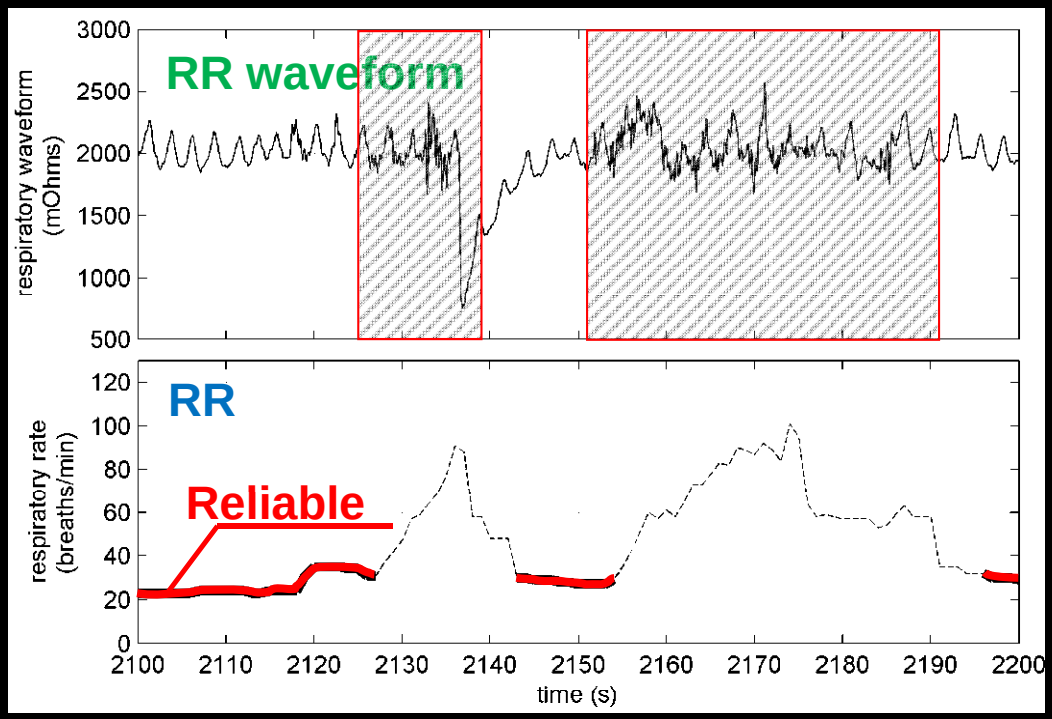
Are vital signs useful for identifying major hemorrhage?

Problem of Data Reliability

Vitals signs, e.g., respiratory rate (RR), often unreliable

- Even in an ICU, monitors usually inaccurate[1]
- Clinicians inaccurate too[2]
- On a helicopter, cannot hear breath sounds[3]

Examples from our database:



RR: 27% reliable

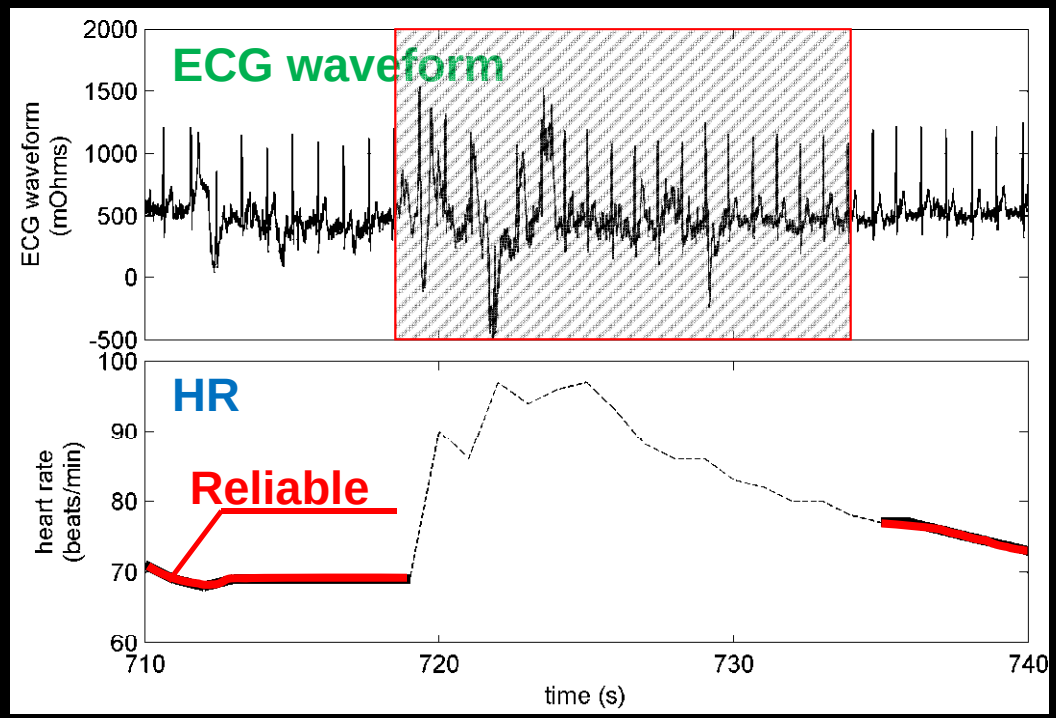
Our automated algorithm matched expert's annotations in 90% of the cases (Chen et al., *Physiol Meas* 2006)

[1]Friesdorf et al., *Int J Clin Mon Comput* (1994)
[2]Lovett et al., *Ann Emerg Med* (2005)
[3]Garner, *JAMA* (1991)

Problem of Data Reliability

Other novel algorithms for other vital signs, reliable vs. unreliable measurements

Example: unreliable ECG waveform & heart rate (HR)

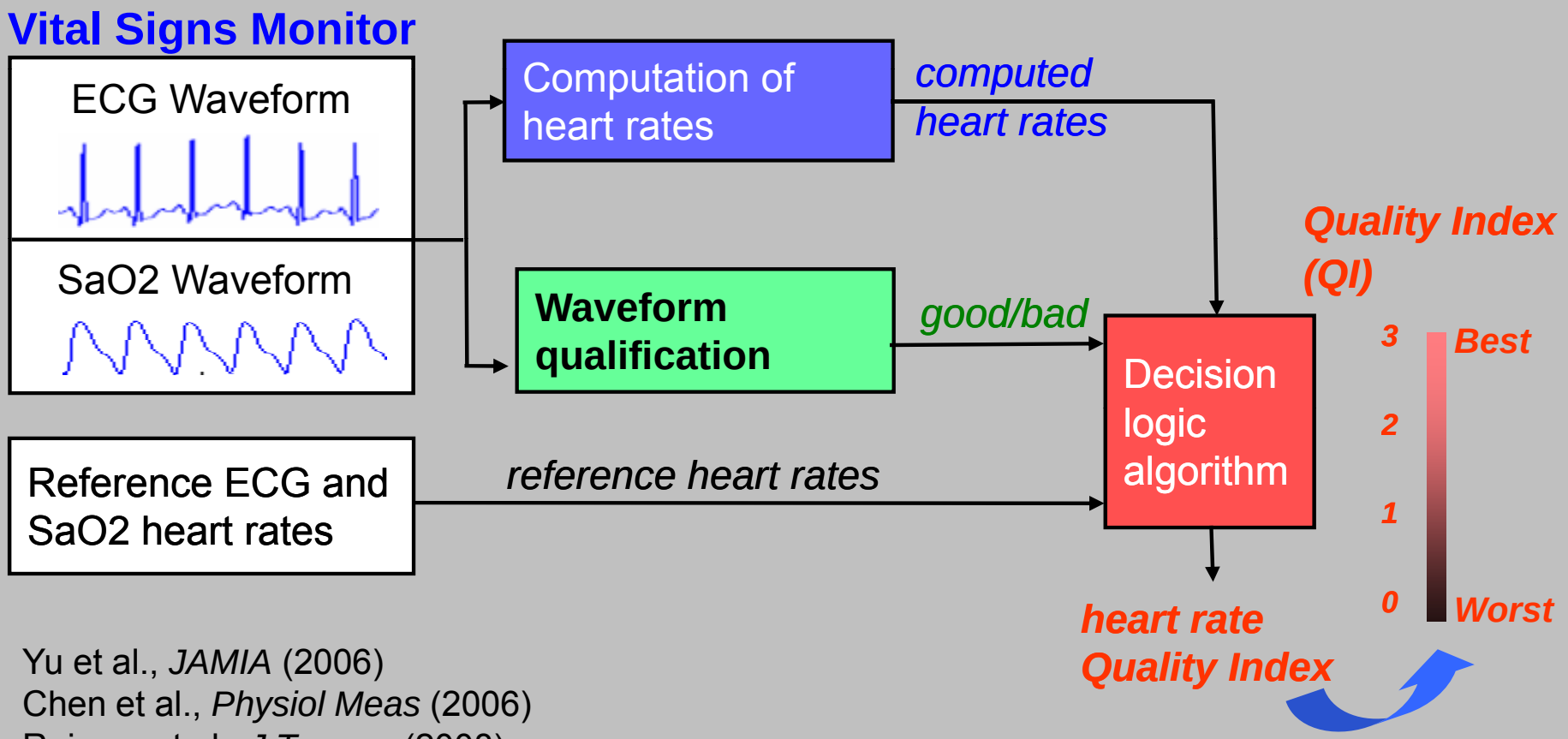


HR: 44% reliable

Our automated algorithm matched expert's annotations >90% of the cases; ~80% agreement between experts (Yu et al., *JAMIA* 2006)

Decision Logic Algorithm

Signal Validation for: ECG, SPO2 (PPG), and RR Waveforms
HR, RR, SaO2, BPs (1-sec data)



Yu et al., *JAMIA* (2006)
Chen et al., *Physiol Meas* (2006)
Reisner et al., *J Trauma* (2008)

"Reliable" vs. "Unreliable" Vital Signs
(as determined by algorithms)

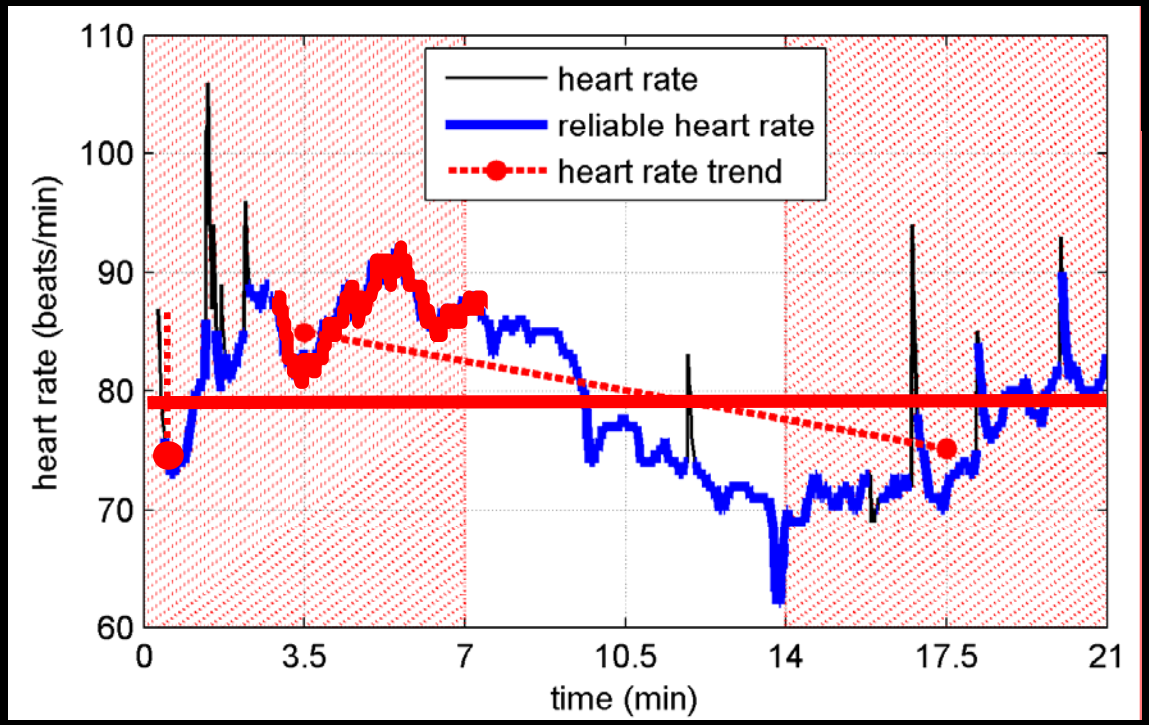
- "Reliable" vital signs superior to "unreliable" vital signs

Vital Sign	ROC AUC (95% CI)*	
	First Data	First Reliable
HR	0.58 (0.51-0.66)	**0.71 (0.64-0.77)**
RR	0.51 (0.39-0.62)	**0.64 (0.56-0.72)**
SaO2	0.58 (0.46-0.69)	0.59 (0.45-0.72)
SBP	0.71 (0.64-0.77)	0.73 (0.67-0.79)
DBP	0.61 (0.53-0.68)	0.63 (0.55-0.70)

*Each AUC was obtained from the largest available population.

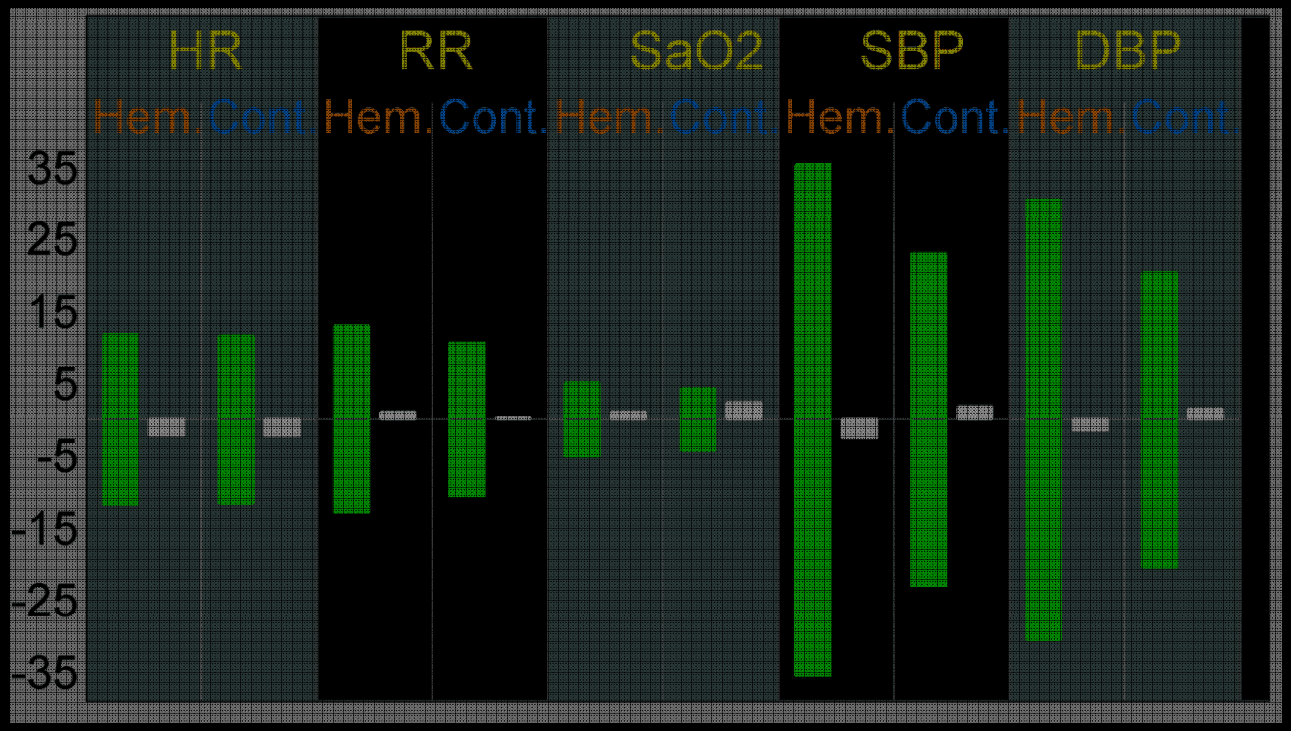
Data Analysis Through Time

- Use the first reliable data?
- Take the average?
- Use trend information?
- Exploit temporal shapes?



Data Analysis Through Time: Trend

- Average variability of vital signs over 21 minutes
- Are trends useful, or is there too much "physiologic noise"?



Chen et al., *Prehospital Emergency Care* (2009)

95% data variability (avg.)
trend (avg.)

Vital Sign	ROC AUC (95% CI)*
ΔHR	0.50 (0.39-0.61)
ΔRR	0.55 (0.41-0.68)
ΔSaO2	0.57 (0.41-0.72)
ΔSBP	0.55 (0.45-0.66)
ΔDBP	0.54 (0.44-0.65)

*Area under the receiver operating characteristic curve and 95% confidence interval.

Prehospital vital-sign trends are *not* discriminatory

Data Analysis Through Time: Avg. Reliable

- Simple but effective:

  A running average to filter-out temporal variability

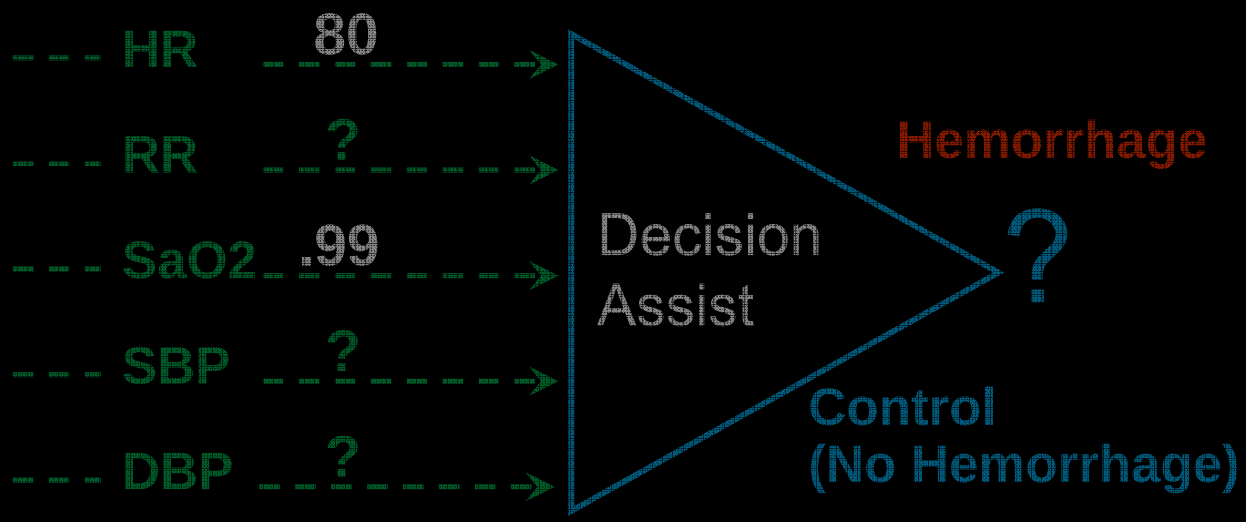
Vital Sign	ROC AUC*		
	First	First Reliable	Average Reliable
HR	0.58 (0.51-0.66)	0.71 (0.64-0.77)	0.74 (0.66-0.81)
RR	0.51 (0.39-0.62)	0.64 (0.56-0.72)	0.68 (0.59-0.76)
SaO2	0.58 (0.46-0.69)	0.59 (0.45-0.72)	0.58 (0.47-0.68)
SBP	0.71 (0.64-0.77)	0.73 (0.67-0.79)	0.78 (0.71-0.84)
DBP	0.61 (0.53-0.68)	0.63 (0.55-0.70)	0.59 (0.50-0.67)

Multivariate Analysis

Can discrimination be improved by simultaneously employing multiple vital signs?

Problem: only **402 (59%)** patients have ≥ 1 sec of reliable vital signs (all 5) **at some time** during transport

Ensemble Classifier



Chen et al., *Journal of Biomedical Informatics* (2008)

Ensemble Classifier only requires *one second* of *any* reliable vital sign during transport [674 patients (99%)]*:

AUC = 0.85 (0.80 – 0.90)

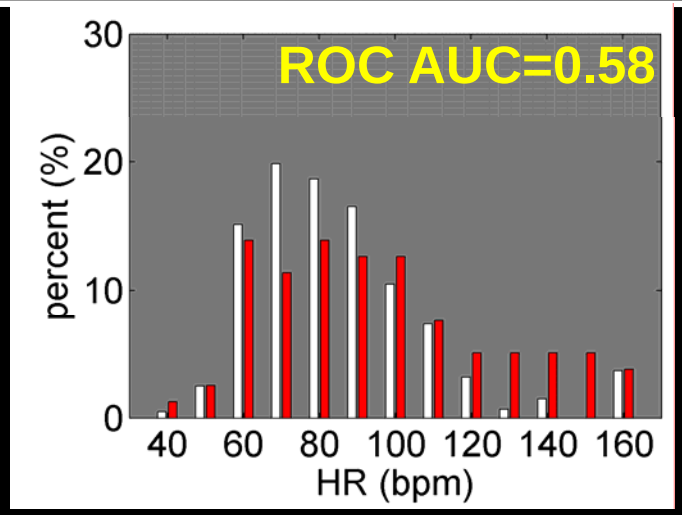
*Patients were randomly divided into non-overlapping training (50%) and testing (50%) sets with balanced classes. The average test AUC and 95% confidence interval of 100 random runs is shown.

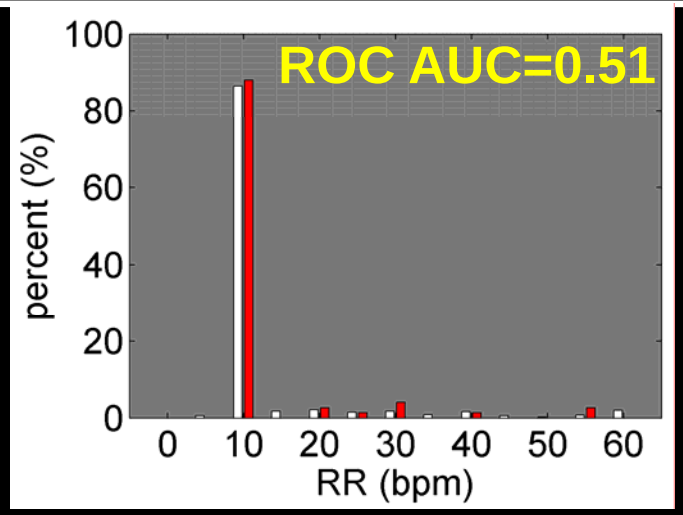
Putting All Together

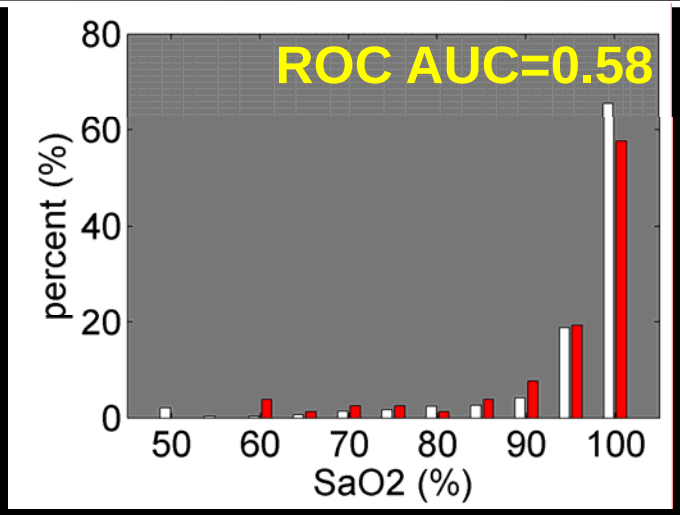
Vital Sign	ROC AUC*		
	First	First Reliable	Average Reliable
HR	0.58 (0.51-0.66)	0.71 (0.64-0.77)	0.74 (0.66-0.81)
RR	0.51 (0.39-0.62)	0.64 (0.56-0.72)	0.68 (0.59-0.76)
SaO2	0.58 (0.46-0.69)	0.59 (0.45-0.72)	0.58 (0.47-0.68)
SBP	0.71 (0.64-0.77)	0.73 (0.67-0.79)	0.78 (0.71-0.84)
DBP	0.61 (0.53-0.68)	0.63 (0.55-0.70)	0.59 (0.50-0.67)
Ensemble	0.71 (0.62-0.82)	0.77 (0.64-0.86)	0.85 (0.80-0.90)

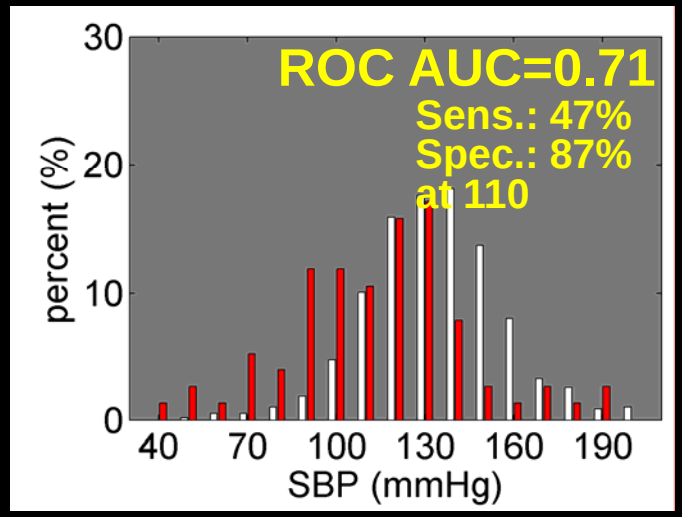
*Each AUC was obtained from the largest available population.

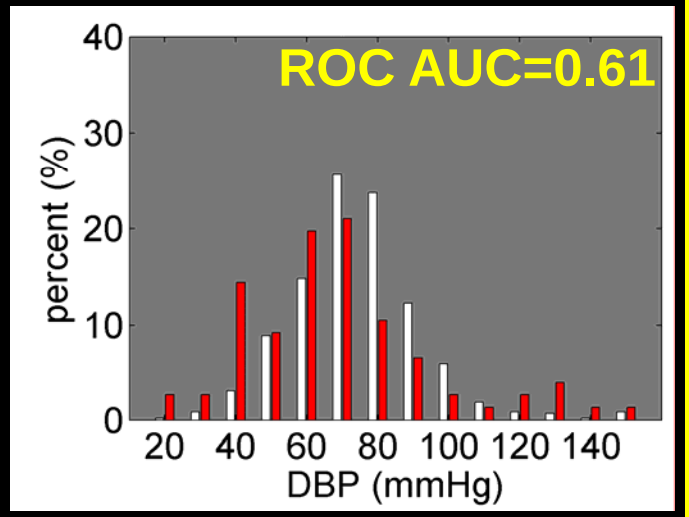
Comparison of First Data vs. Ensemble

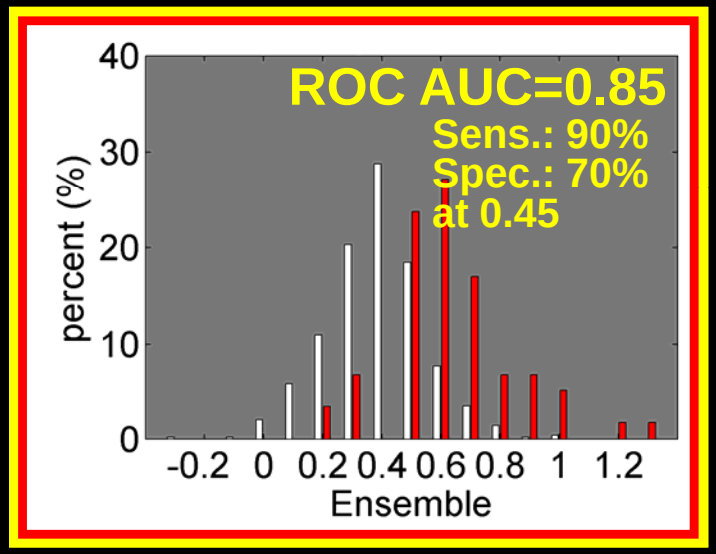












control

hemorrhage

Improved discrimination with multivariate, *Ensemble Classifier*

Summary

Established a benchmark for basic vital signs

- **For Major Hemorrhage decision support**
  - ROC AUC of 0.85 (0.80 – 0.90 with 95% CI)
- **To be considered, other sensor modalities and parameters need to surpass benchmark**

Next Steps

- **Employ decision support to predict clinical outcomes during transport of trauma patients (APPRAISE)**

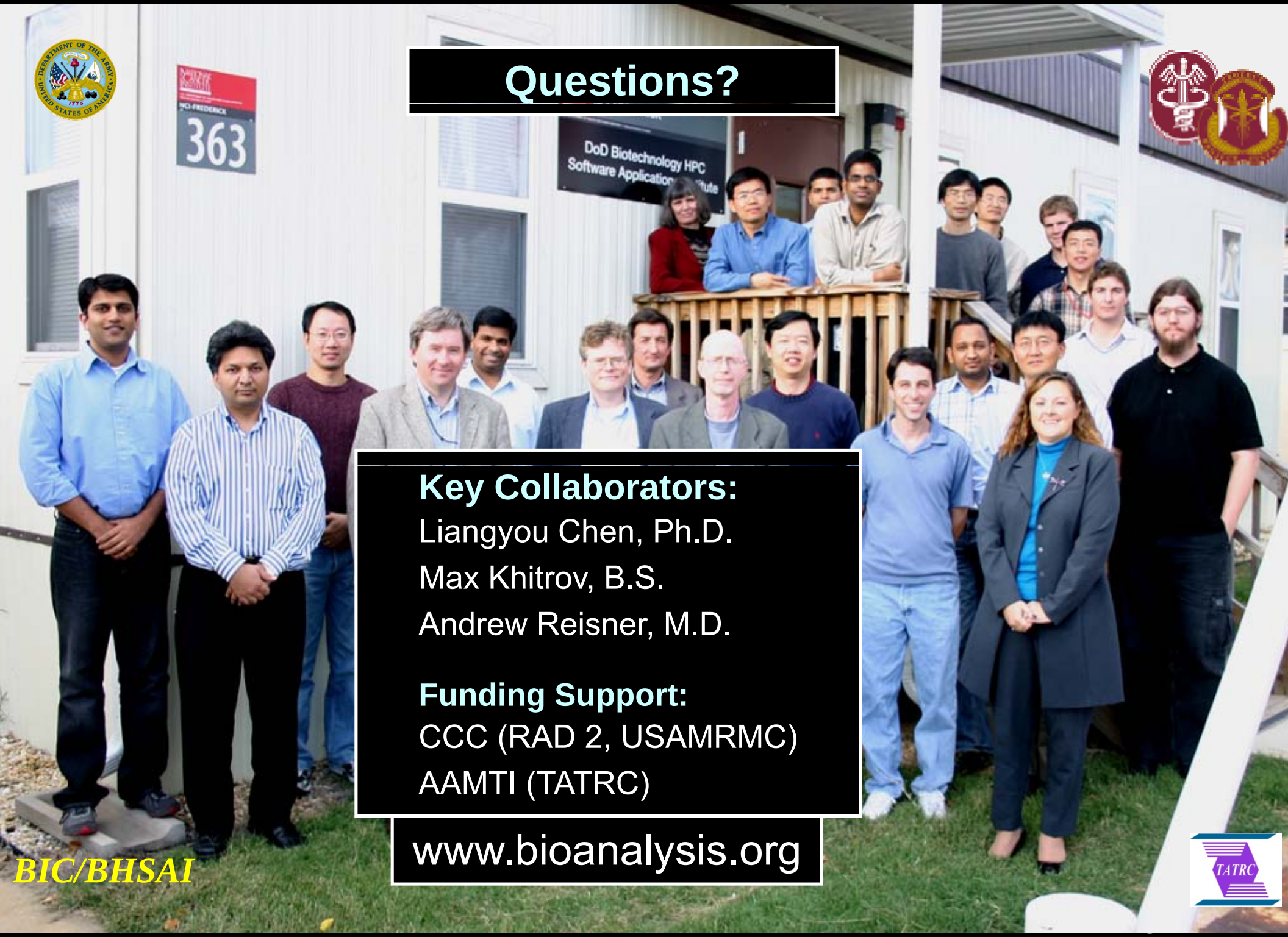
- **Evaluate other sensor modalities against benchmarked results**

Boston Medflight

APPRAISE

Propaq Monitor

Ruggedized PC & Algorithms



Questions?

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