Welcome to

2.160

Identification, Estimation, and Learning

3-0-9 H-Level Graduate Credit

Prerequisite: 2.151 or similar subject

Reference Books

★★★

Lennart Ljung, “System Identification: Theory for the User, Second Edition”, Prentice-Hall 1999

★★

Graham Goodwin and Kwai Sang Sin, “Adaptive Filtering, Prediction, and Control”, Prentice-Hall 1984

★

Kenneth Burnham and David Anderson, “Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach, Second Edition”, Springer 1998

Lecture Notes

- Provided for every lecture
- Helpful
- Intensive and extensive
- Covers a lot of topics
- Examples
- Background materials and review
- Read them before going to the reference books

Grading

• Mid-Term exam, (12:30 pm – 2:30 pm, April 3, 2006)	30%
• End-of-Term exam (12:30 pm – 2:30 pm, May 17, 2006)	30%
• Homework Assignment (8 ~ 9 assignments)	20 %
• Term project (Suggested topics and guidelines will be provided.)	20%
Total	100%

Problem Set Weekly Schedule:

W	R	F	Sa	Su	M	T	W
Out		Read notes & PS		Do It	Just Do It	Asada Office H	Due

H. Harry Asada

- Specializes in Robotics, Biomedical Engineering
- Regularly teaches
  - 2.12 Introduction to Robotics
  - 2.151 Advanced System Dynamics and Control
  - 2.165 Robotics
  - 2.14 Feedback Control

Biologically-Inspired Actuators

Ball-Wheel
Holonomic Wheelchair
US Patent 5,927,423

Fingernail Sensors
US Patent 6,236,037
US Patent 6,388,247

RHOMBUS
Hybrid Bed/Wheelchair
US Patent 6,135,228

Repositioning Active Bed Sheet

Surface Wave Actuators
US Patent 5,953,773

I am an inventor.

Wireless Networking
US Patent 6,553,535

Wearable Goniometry

ABP Estimation
US Patent 6,413,223

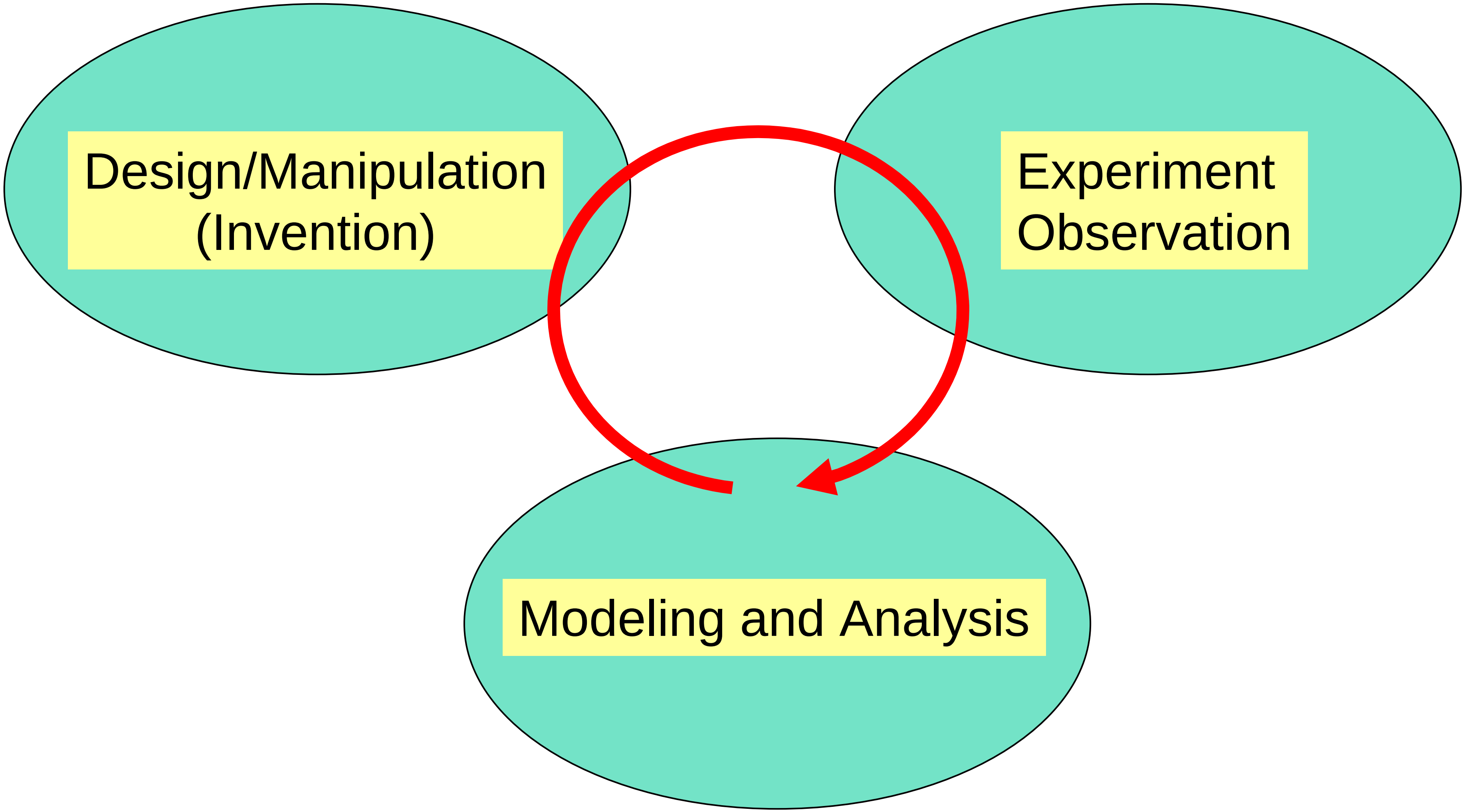
Ring Sensor
US Patent 6,402,690
US Patent 5,964,701
US Patent 6,699,199

Cable-Free Smart Vest

Driver Monitoring

Health Chair
US Patent 6,947,781

Wearable Health Monitoring

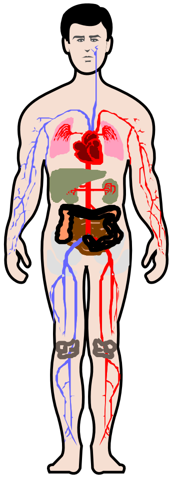


Basic Engineering Methodology

2.160

Identification, Estimation, and Learning

Mathematical models of real-world systems are often too difficult to build based on first principles ***alone***.



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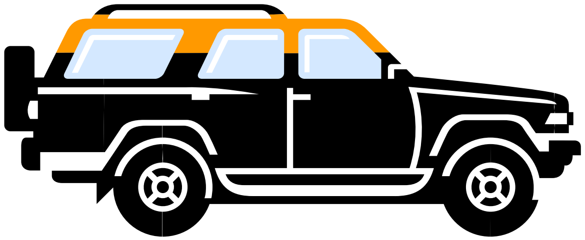

Figure by MIT OCW.

System Identification;
"Let the data speak about the system".

Courtesy of Prof. Asada. Used with permission.

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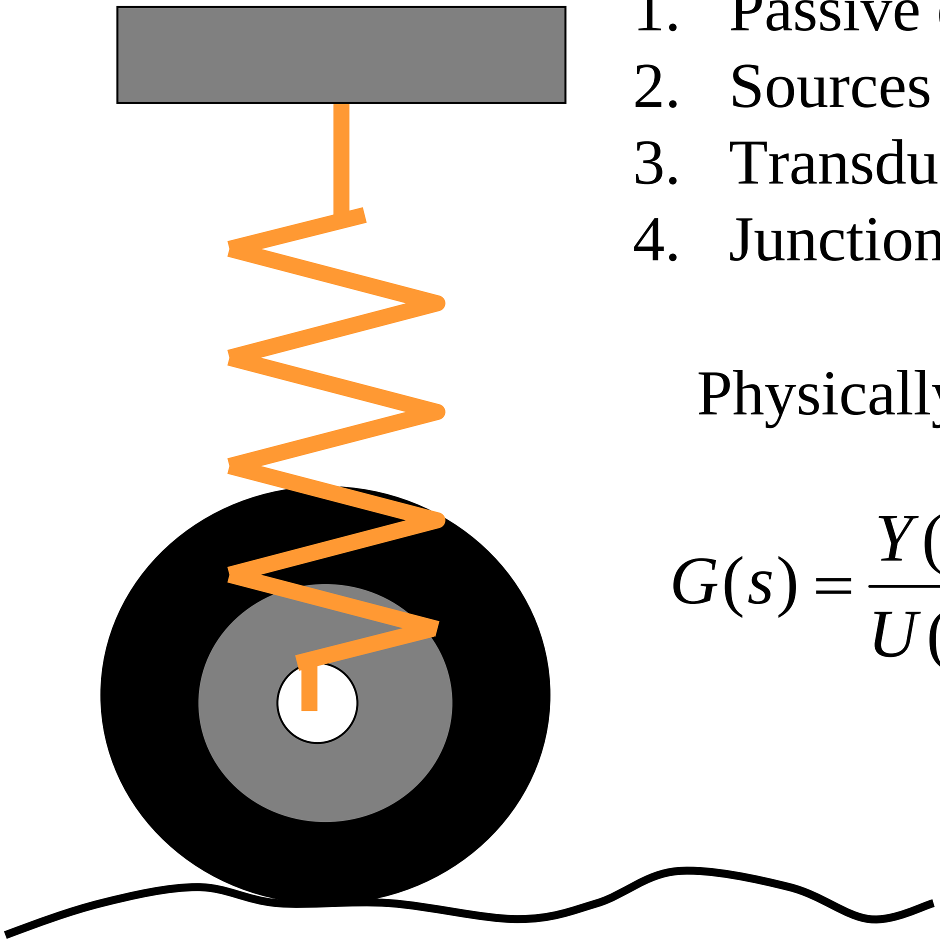
HVAC

Physical Modeling : 2.151



1. Passive elements: mass, damper, spring
2. Sources
3. Transducers
4. Junction structure

Physically meaningful parameters

$$G(s) = \frac{Y(s)}{U(s)} = \frac{b_0 s^m + b_1 s^{m-1} + \cdots + b_m}{s^n + a_1 s^{n-1} + \cdots + a_n}$$

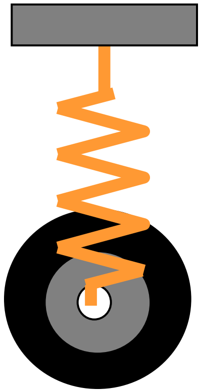
$$a_i = a_i(M, B, K)$$

$$b_i = b_i(M, B, K)$$

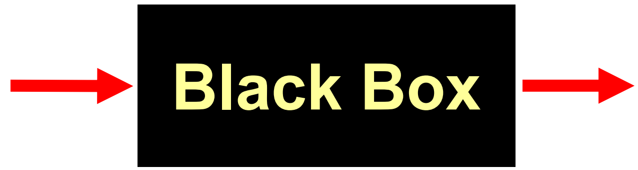
System Identification

$$G(s) = \frac{Y(s)}{U(s)} = \frac{b_0 s^m + b_1 s^{m-1} + \cdots + b_m}{s^n + a_1 s^{n-1} + \cdots + a_n}$$

Physical modeling



Comparison



Pros
1. Physical insight and knowledge
2. Modeling a conceived system before hardware is built

Cons
1. Often leads to high system order with too many parameters
2. Input-output model has a complex parameter structure
3. Not convenient for parameter tuning
4. Complex system; too difficult to analyze

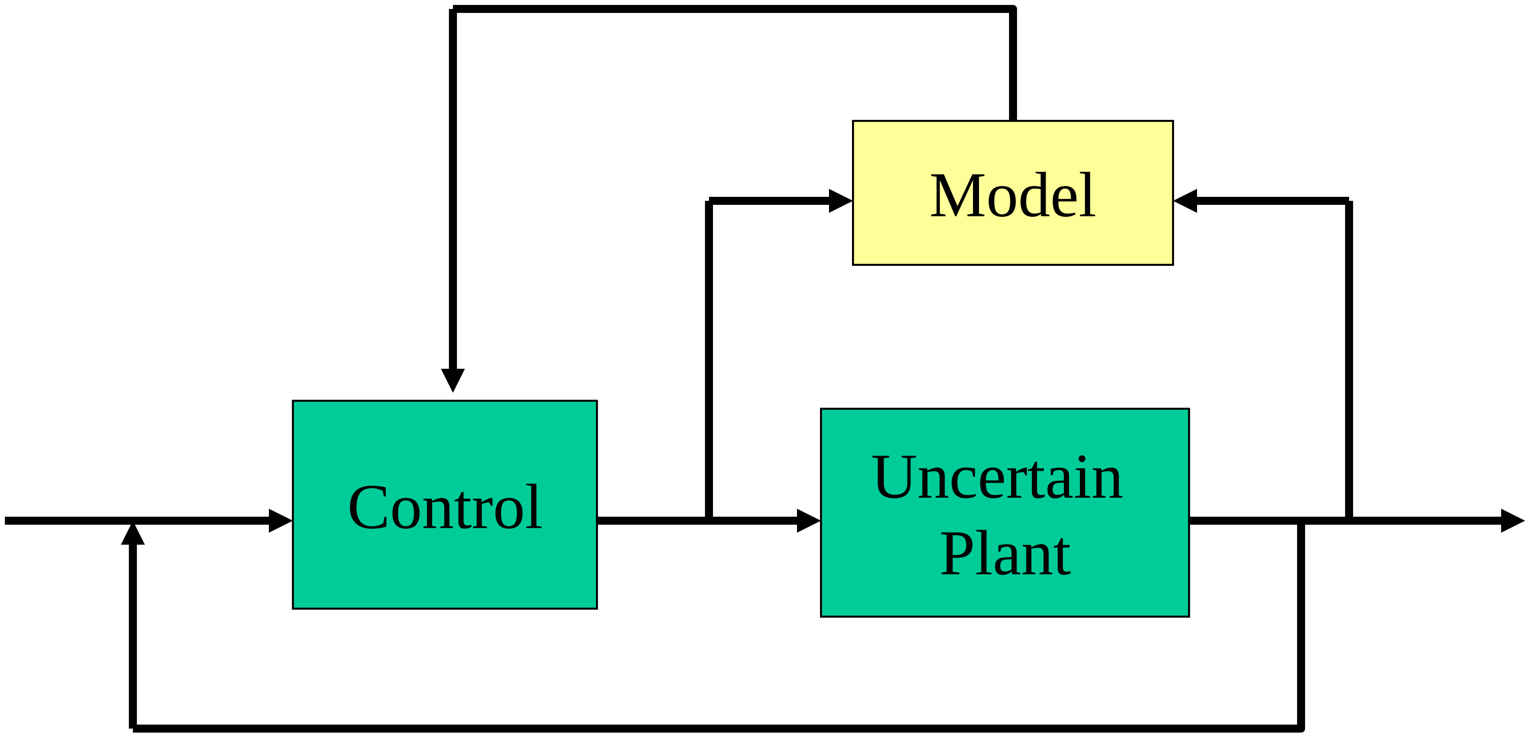
Pros
1. Close to the actual input-output behavior
2. Convenient structure for parameter tuning
3. Useful for complex systems; too difficult to build physical model

Cons
1. No direct connection to physical parameters
2. No solid ground to support a model structure
3. Not available until an actual system has been built

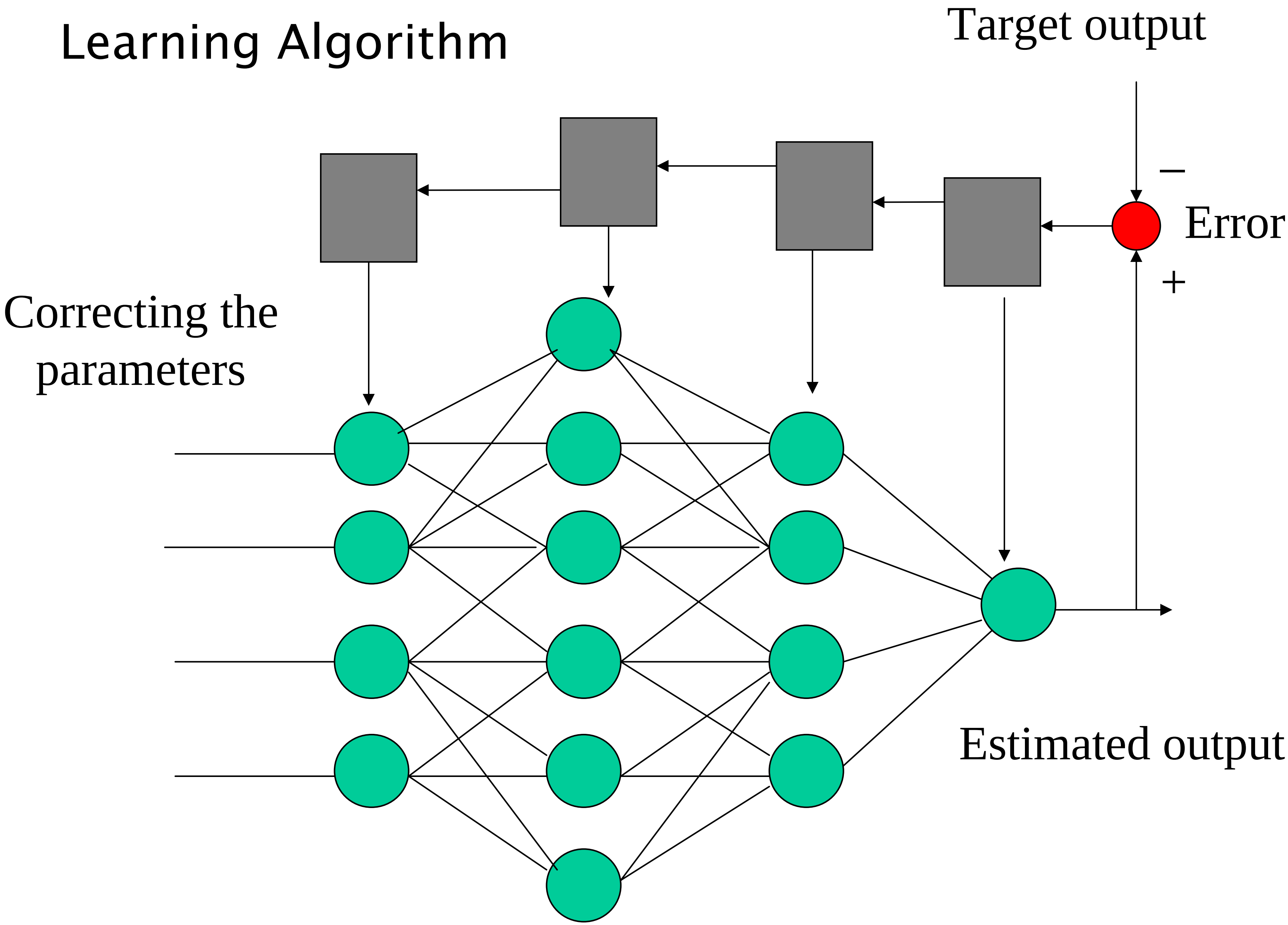
System identification and estimation: Underpinning Theory of

- Adaptive control
- Learning algorithms
- Robust control
- Adaptive filters
- Navigation and guidance

Adaptive Control



Learning Algorithm



Successfully Applied to:

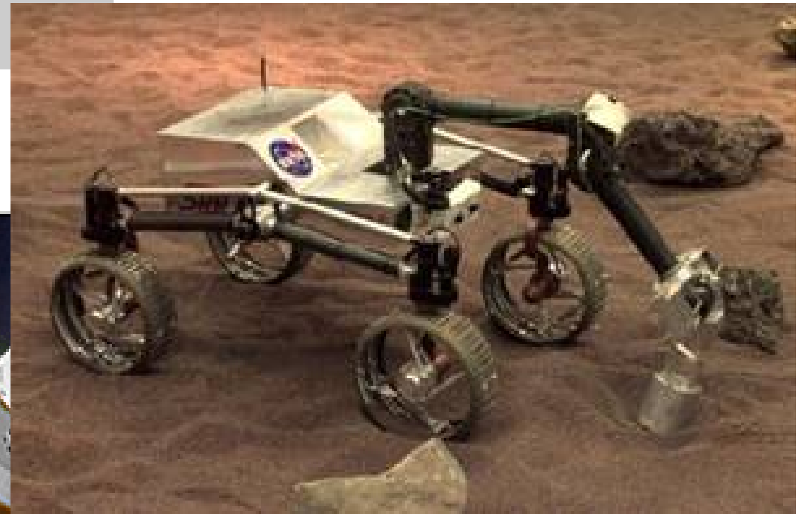
- The Apollo project: Kalman filter
- Mobile robot navigation
- Robot skill learning
- Cardiovascular monitoring
- Air conditioner control
- CCV: Control configured vehicle
- Speech recognition
- Image processing

National Aeronautics and Space Administration

The Apollo project: Kalman filter

Estimation and Learning of Ground Characteristics
Professor S. Dubowsky

National Aeronautics
and Space Administration



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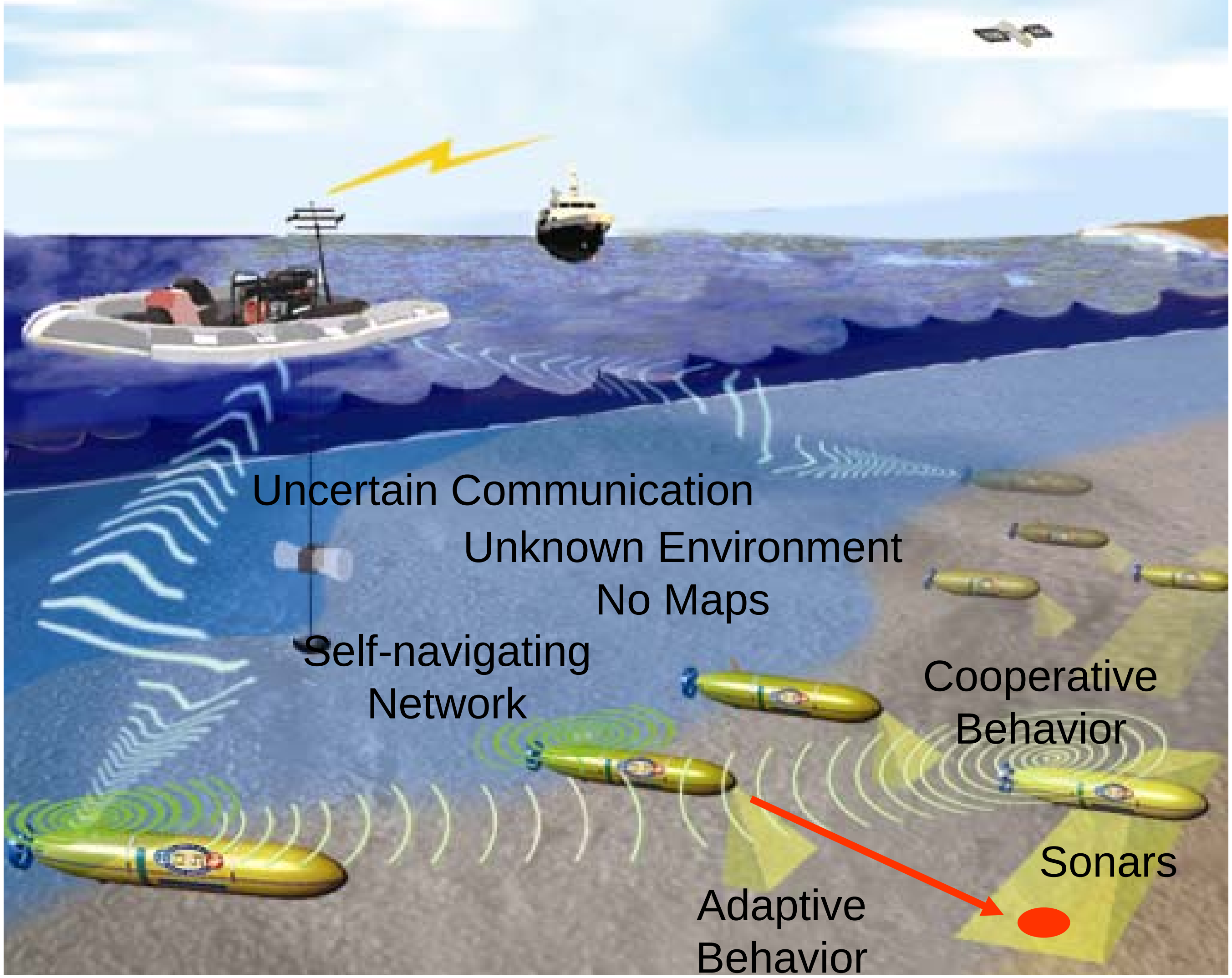
Mobile Sensor Network

Professor John Leonard



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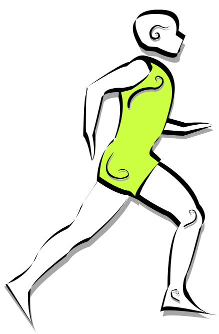
Wearable Sensors: Noise Cancellation Using Accelerometers



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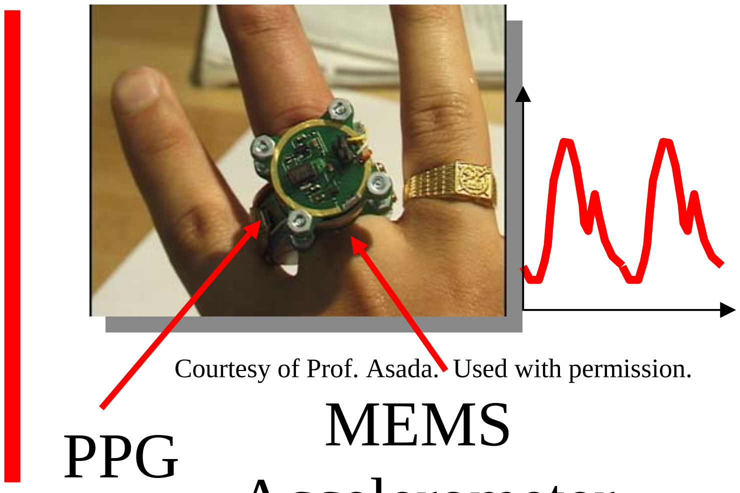
Body motion



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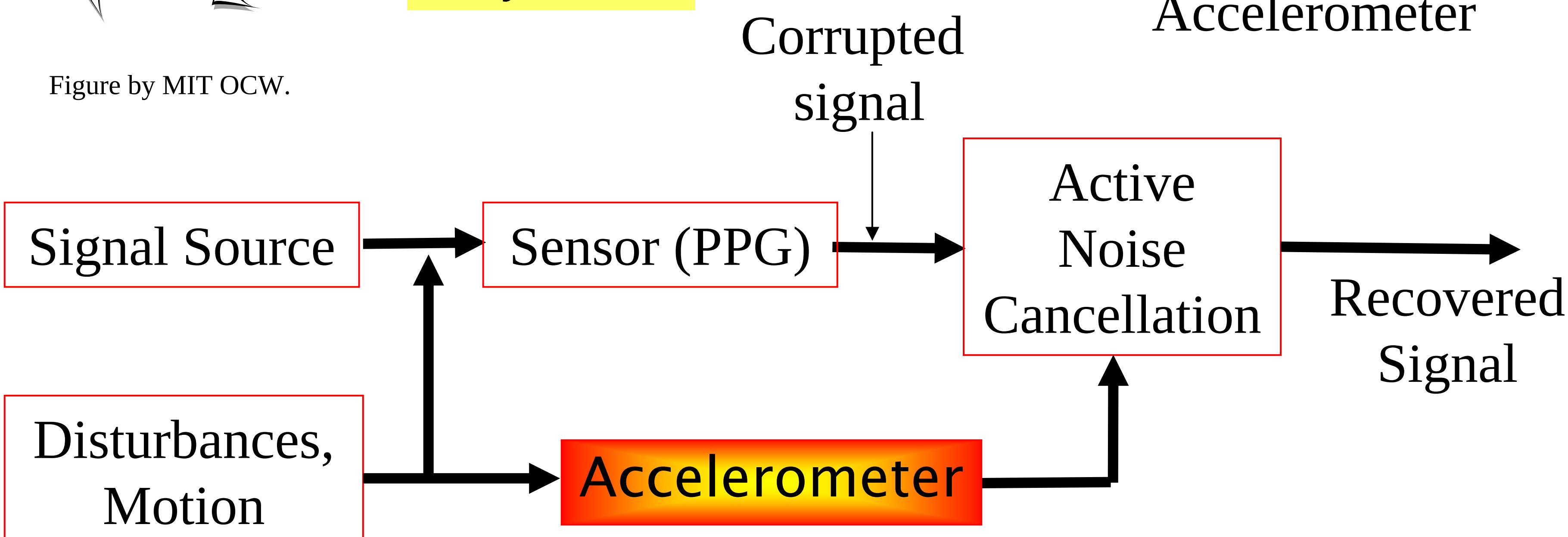
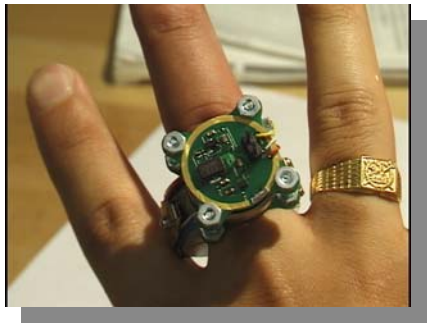


Active Noise Cancellation



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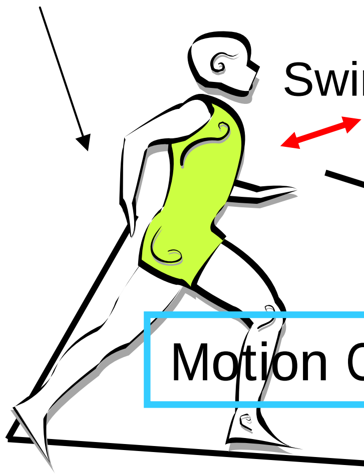

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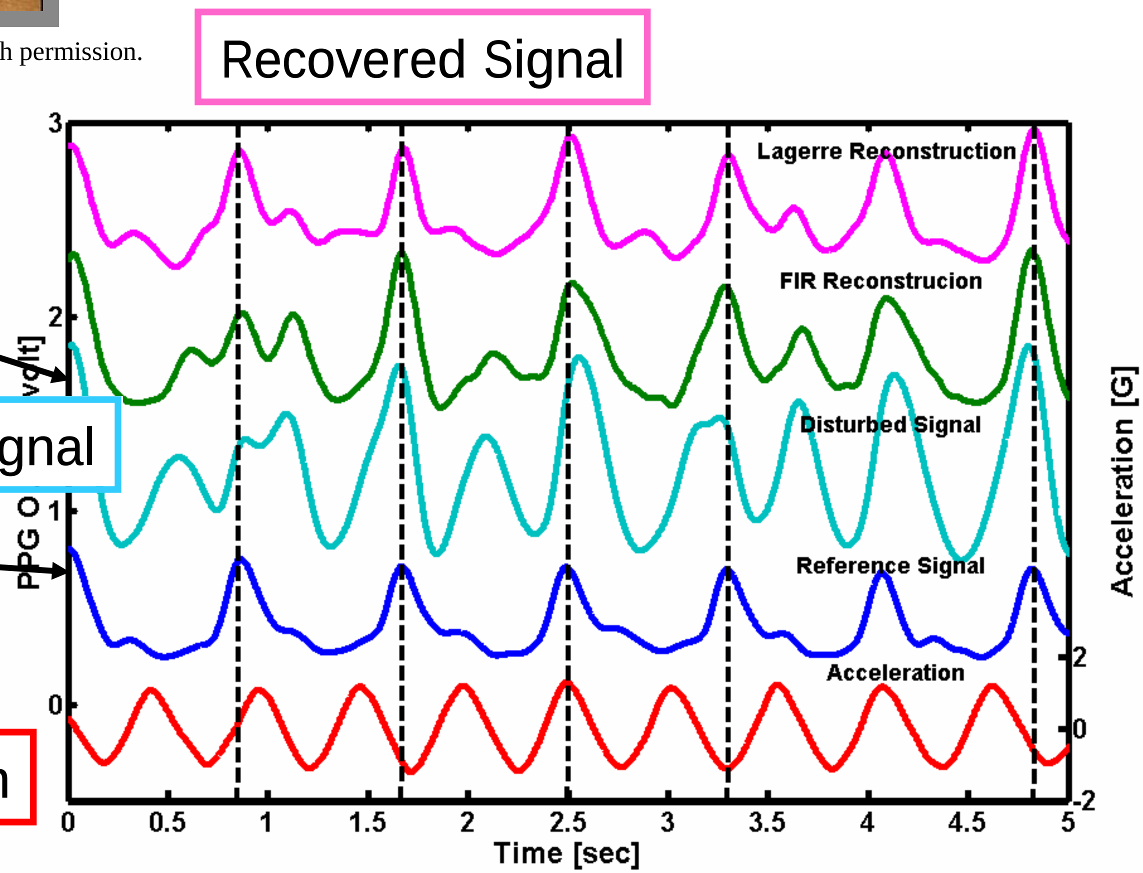
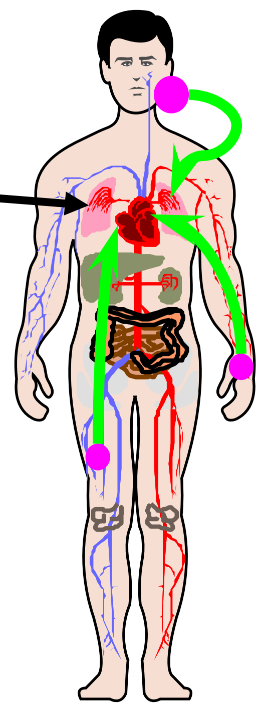


Cardiovascular Monitoring: Invasive Catheter vs. Noninvasive Peripheral Sensors

Invasive:
Catheterization

Intensive care Unit



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Noninvasive:
peripheral sensors

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Arterial Tonometer

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PPG Ring Sensor

Wearable

Deriving 'central' information
from 'peripheral' noninvasive measurements

Animal Study

O_2 Saturation

Right
Axillary
Pressure

Left Radial

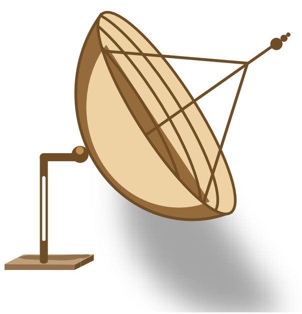
Aortic Flow
For Comparison

Photo of surgery on a pig. Removed for copyright reasons.

Right Iliac Pressure

Multi-channel Blind System ID

A broadcast signal is transmitted through multiple paths and observed simultaneously by multiple receivers at different locations



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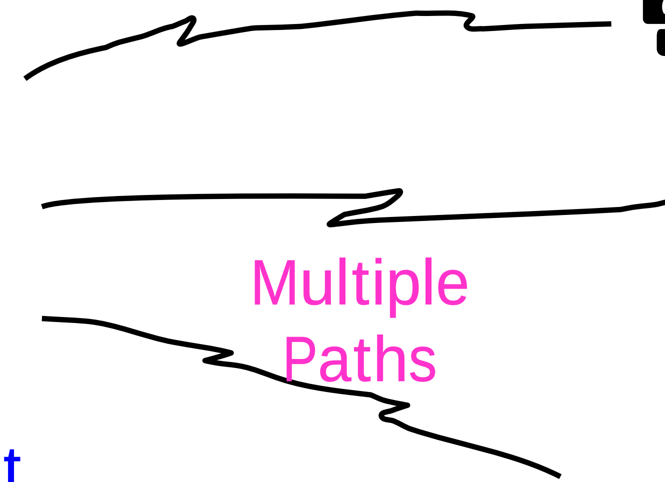
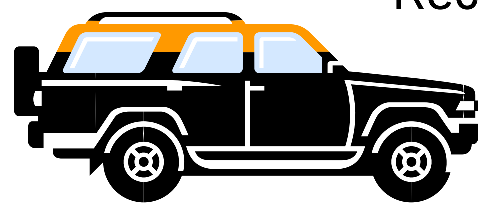
Broadcast Signal



Multiple Paths

Receiver 1



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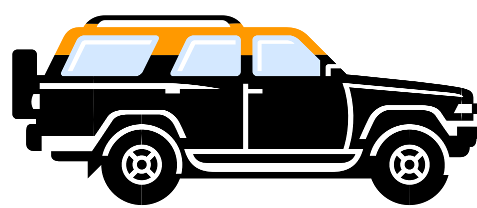
Multiple Receivers

Receiver M



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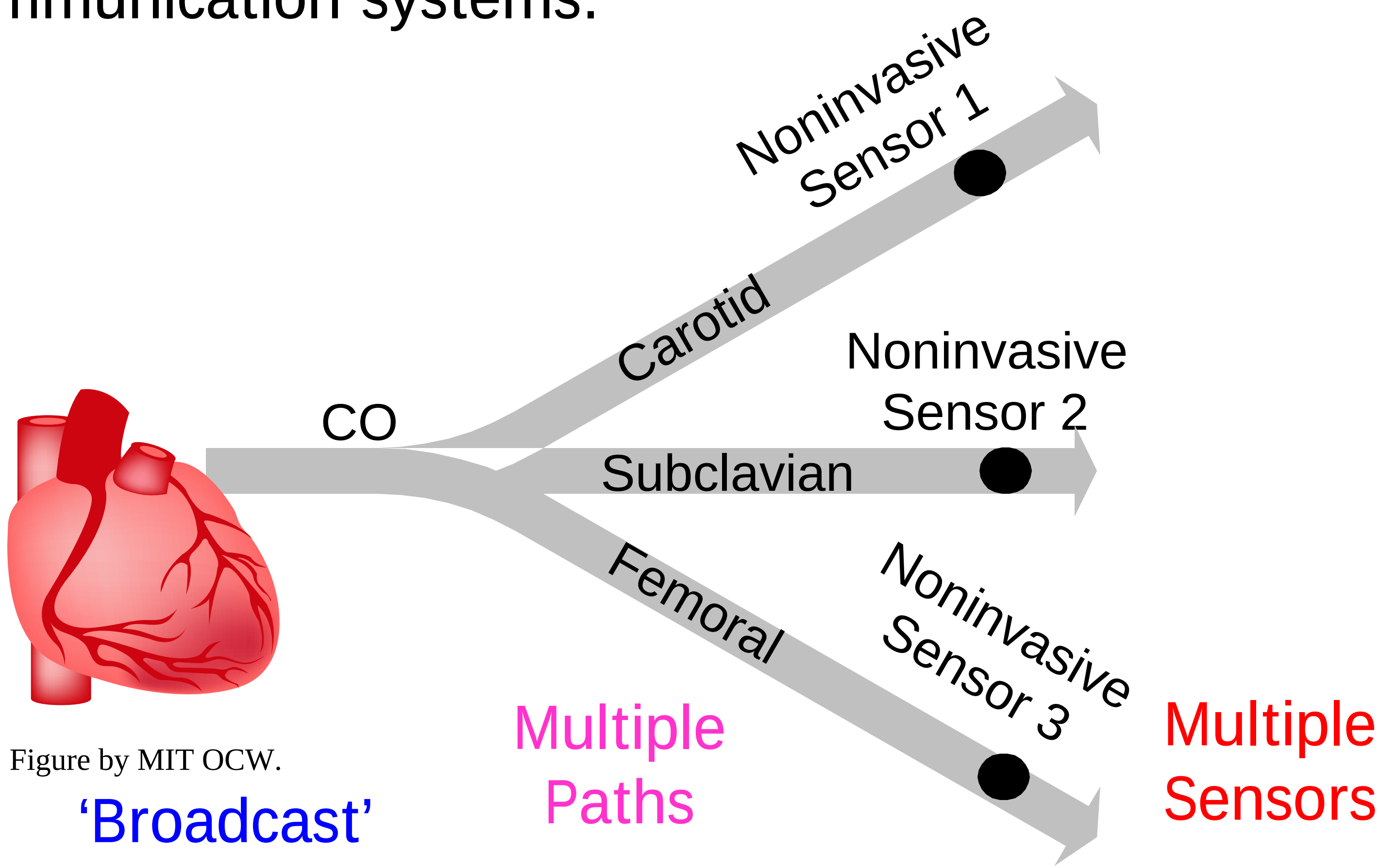
Cardiovascular MBSI

Cardiovascular system has a structure similar to wireless communication systems.



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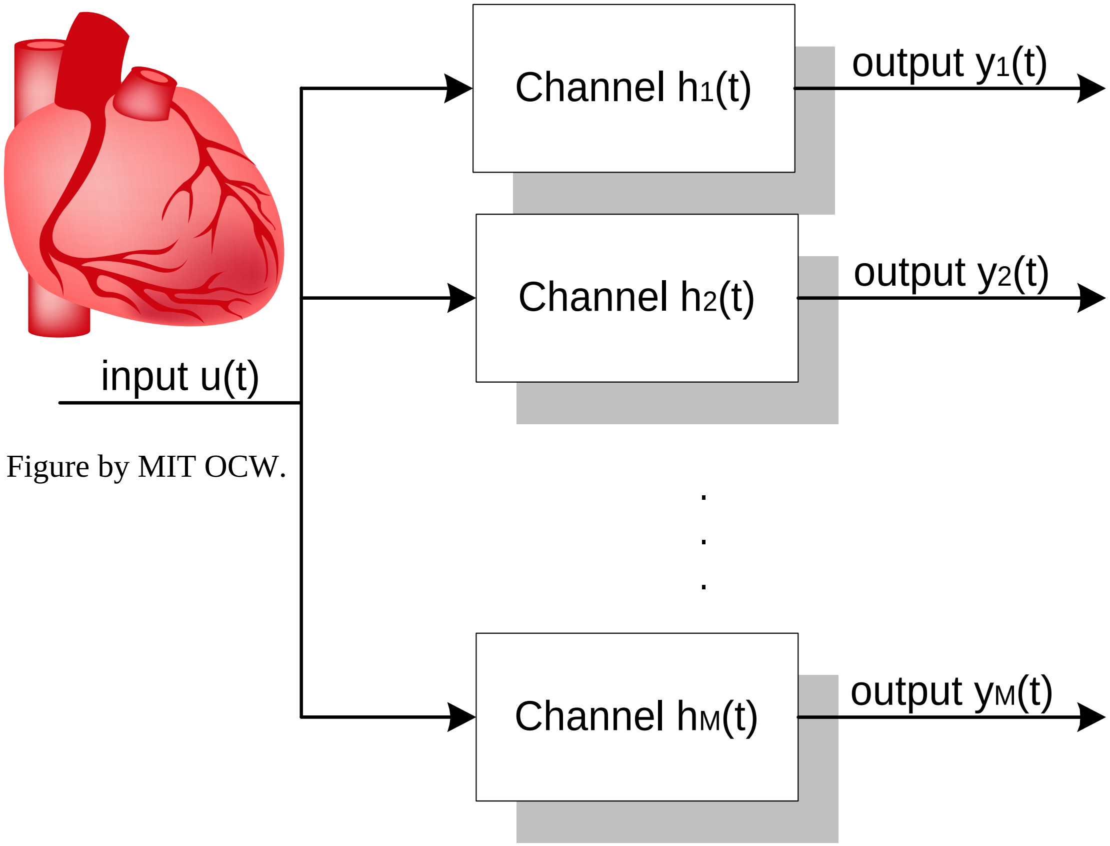
‘Broadcast’ Signal

Multi-channel Blind System Identification (MBSI)- A Magic



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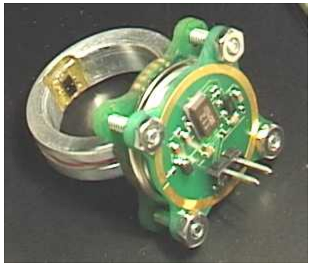

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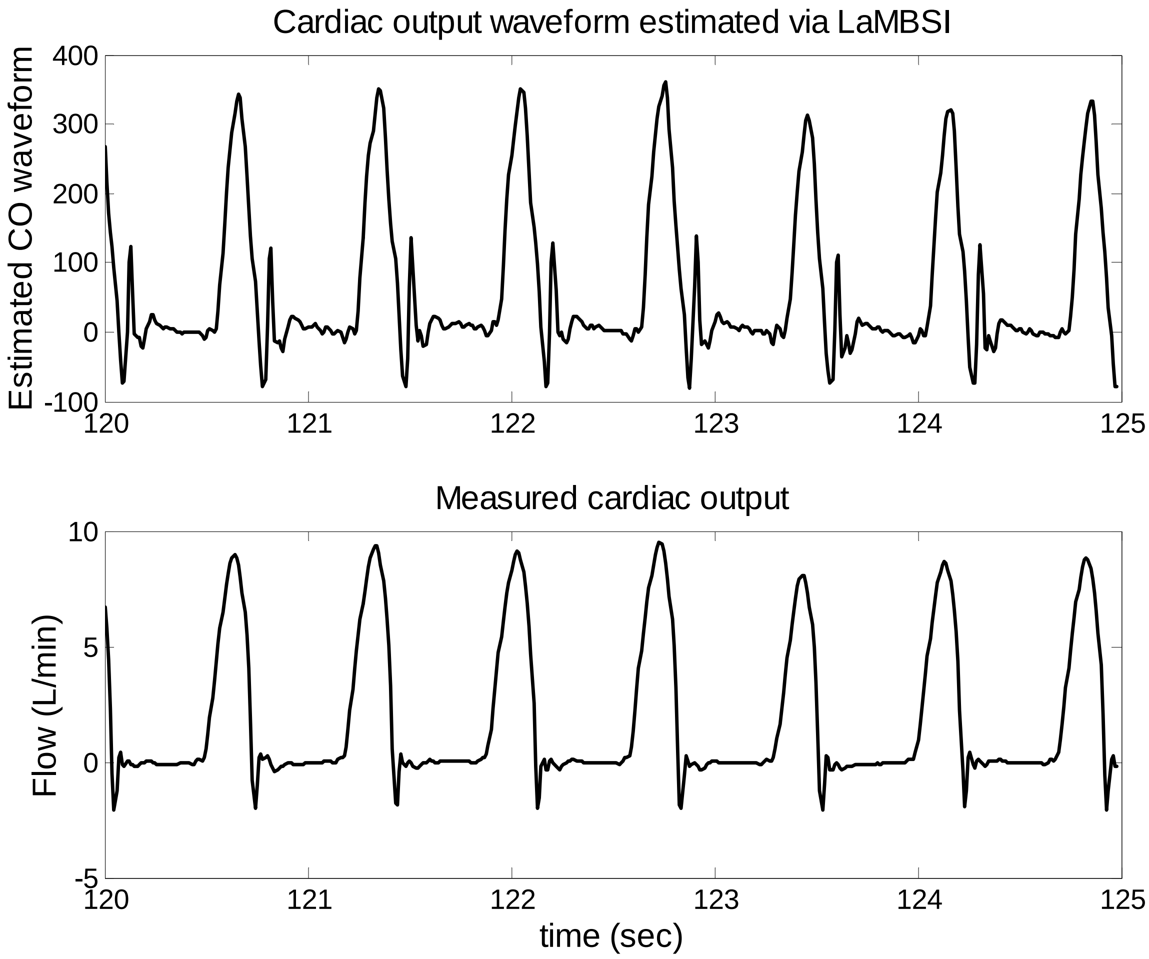
Key Feature

All the channels are driven by the SAME input

Cardiac output waveform estimation using the Laguerre deconvolution algorithm



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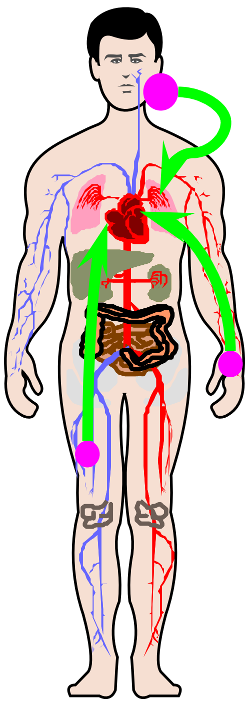

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