Eldercare and Rehabilitation Technology for Better Health

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Research supported by NIH, NSF, AHRQ, AOA & Alzheimer's Association

Center for Eldercare and Rehabilitation Technology

Kinect sensor

Injury prevention

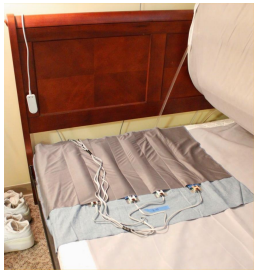
Sports Doctors
Physical Therapists

Depth sensor

Doppler radar

Motion sensors

Remote physical therapy

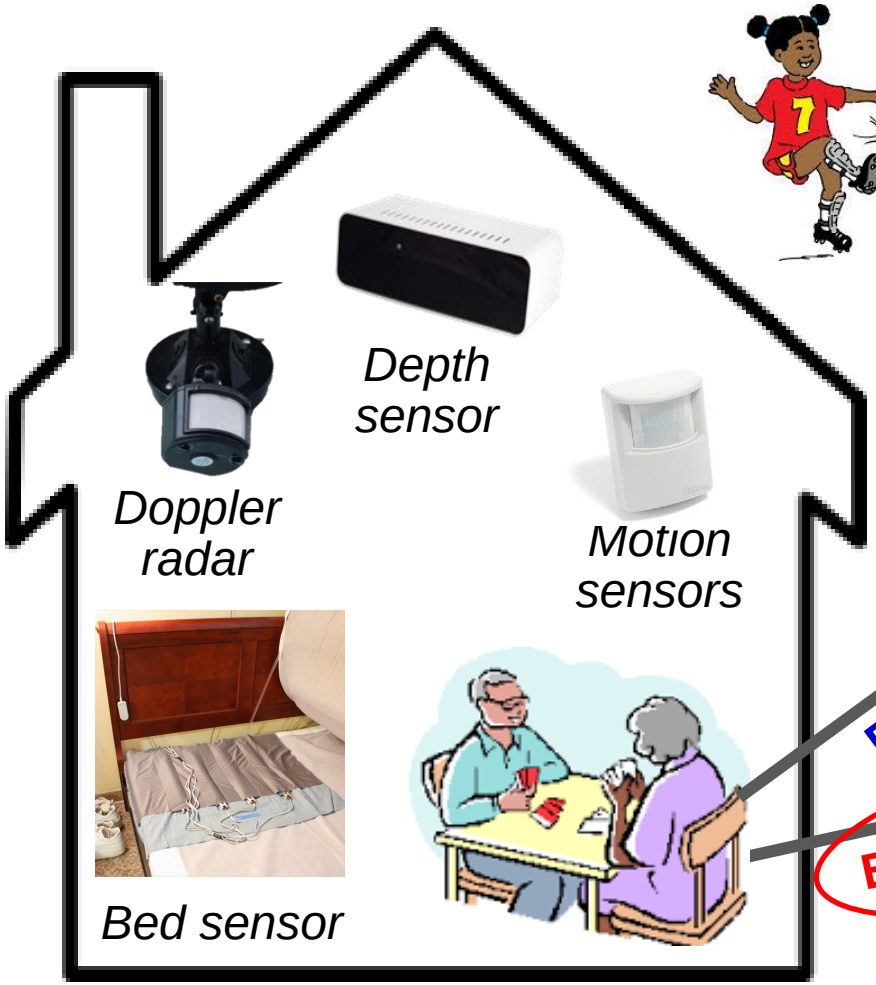


Bed sensor

Early illness detection

Nurses
Social Workers

Center for Eldercare and Rehabilitation Technology



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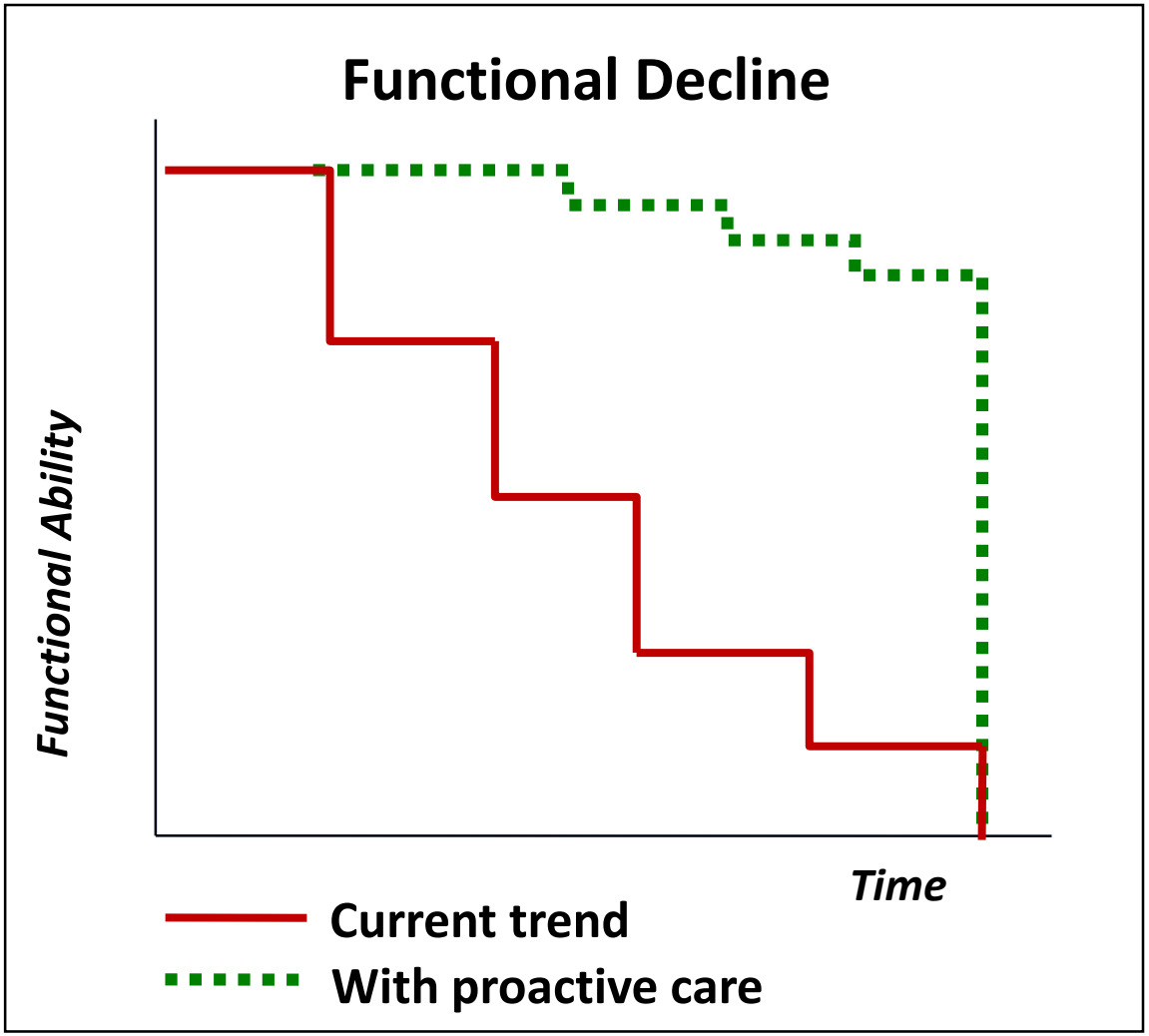
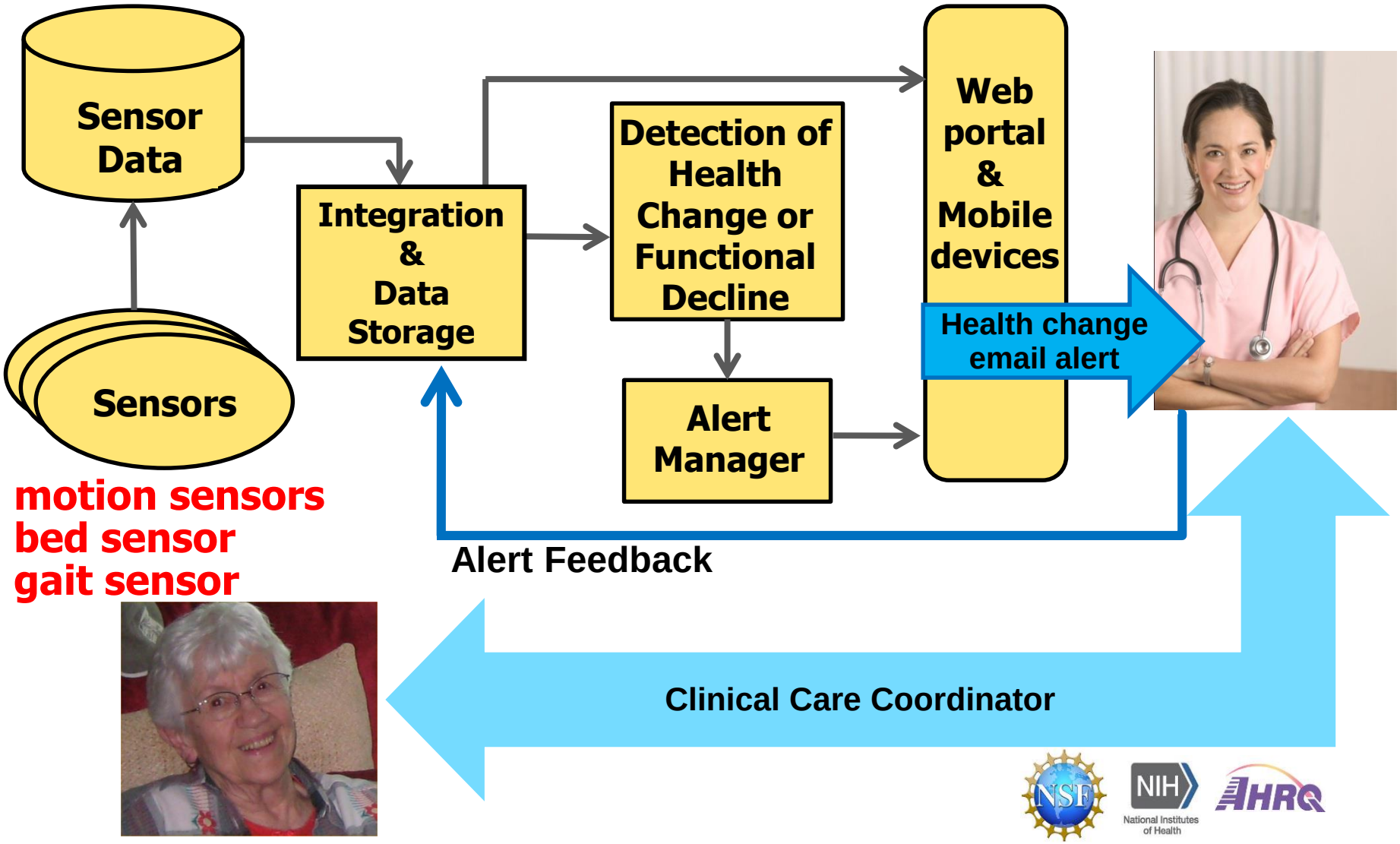
Squaring the Life Curve



Rantz et al, *Nursing Outlook*, 2005

Sensor Network for Health Alerts

clinical decision support system



NSF NIH National Institutes of Health AHRQ

Skubic, *et al.*, *IEEE J. of Trans. Eng. in Health & Medicine*, 2015

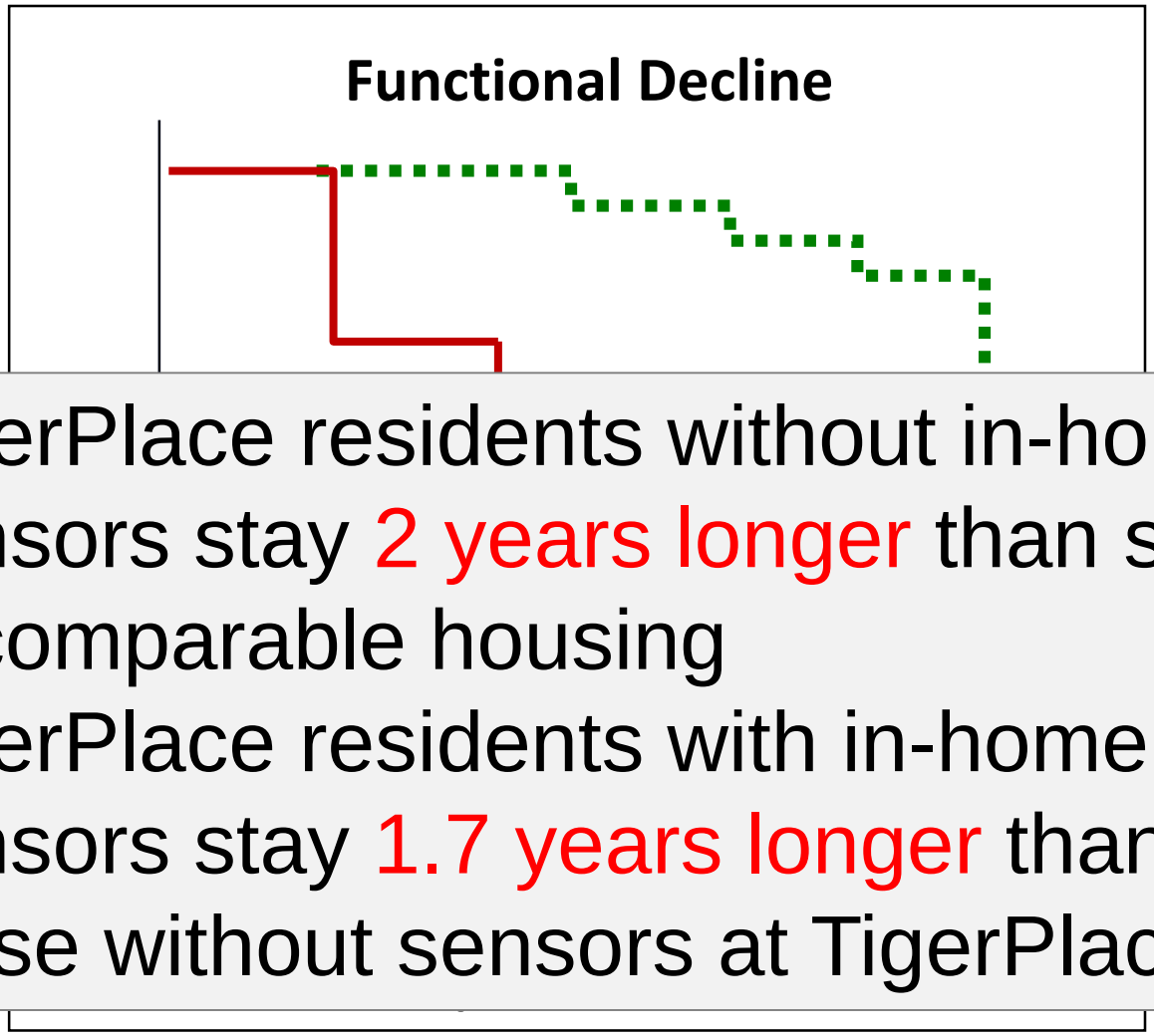
TigerPlace

54 apartments

Designed for Aging in Place

- 65 residents, aged from about 70 to 100
- 90% have a chronic illness
  - e.g., arthritis, heart disease, diabetes, stroke risk
- 60% have multiple chronic illnesses
- Some early stage Alzheimers
- 35% use a walker; some wheelchairs
- Residents tend to be socially active

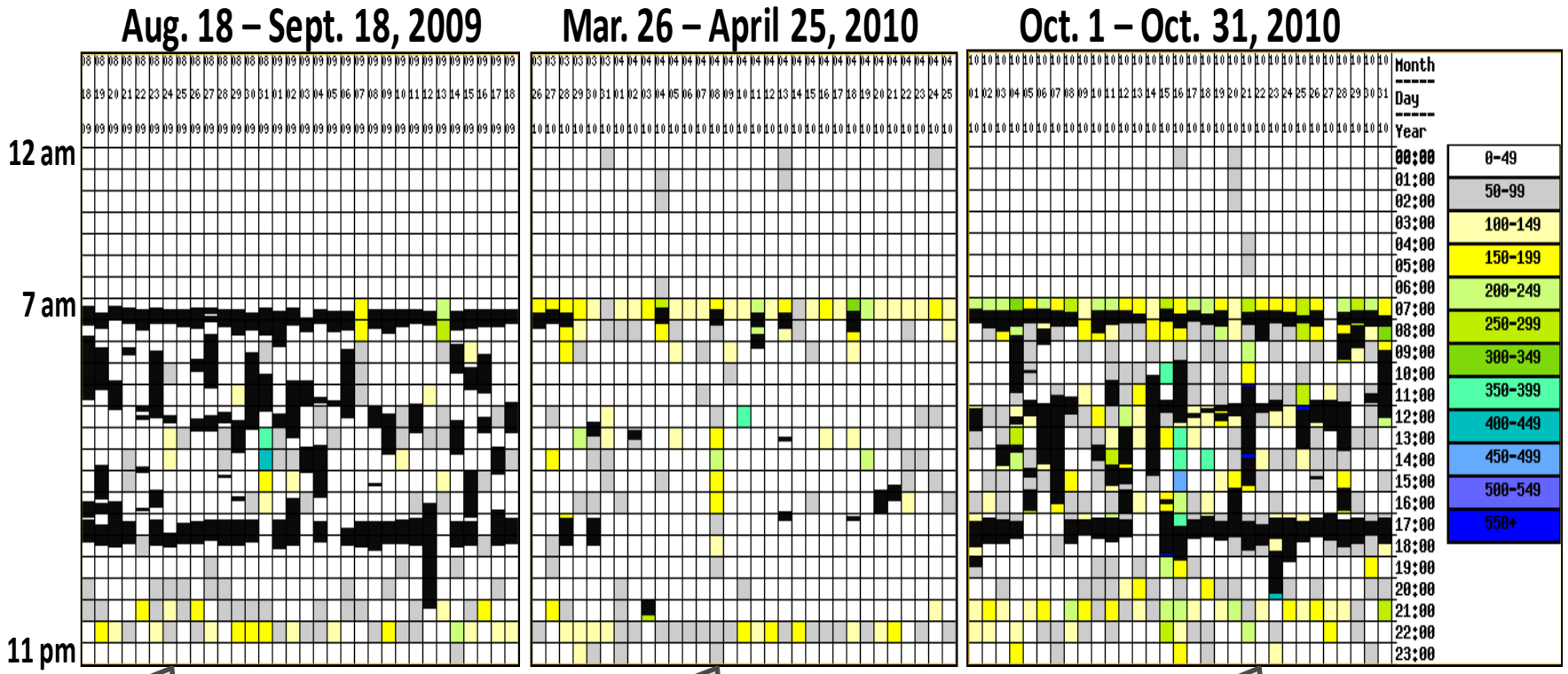
Squaring the Life Curve



- TigerPlace residents without in-home sensors stay 2 years longer than seniors in comparable housing
- TigerPlace residents with in-home sensors stay 1.7 years longer than those without sensors at TigerPlace

Rantz et al, *Nursing Outlook*, 2005, 2015

Case Study: Diagnosis & history of depression



Depression managed & followed by a geriatric psychiatrist

After personal losses resident reported low energy, had trouble eating, and stopped going to the dining room

After intervention, resident's activity pattern increased

S. Wang et al., *JBHI*, 2012; Galambos et al., *Gerontechnology*, 2013

illnesses detected early

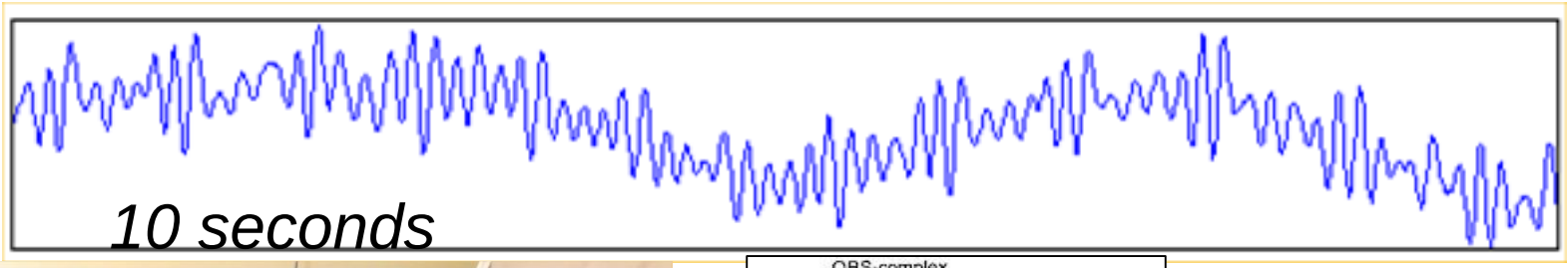
- urinary tract infections
- pneumonia & other upper respiratory infections
- increasing congestive heart failure
- pain post hospitalization
- delirium
- low blood sugar

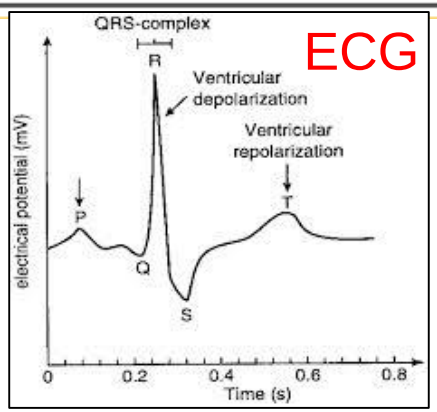
Uses a model of early illness recognition
to generalize across different health problems

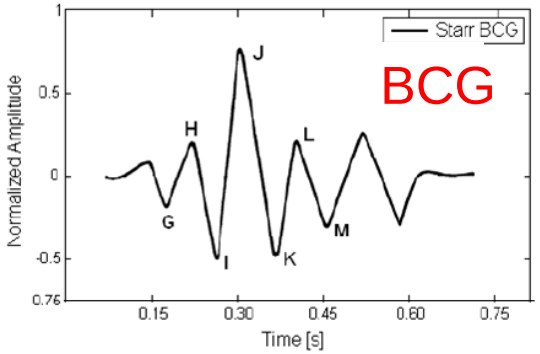
Rantz et al., *J of Gerontological Nursing*, 2012.

MU Hydraulic Bed Sensor

Captures the ballistocardiogram & respiration



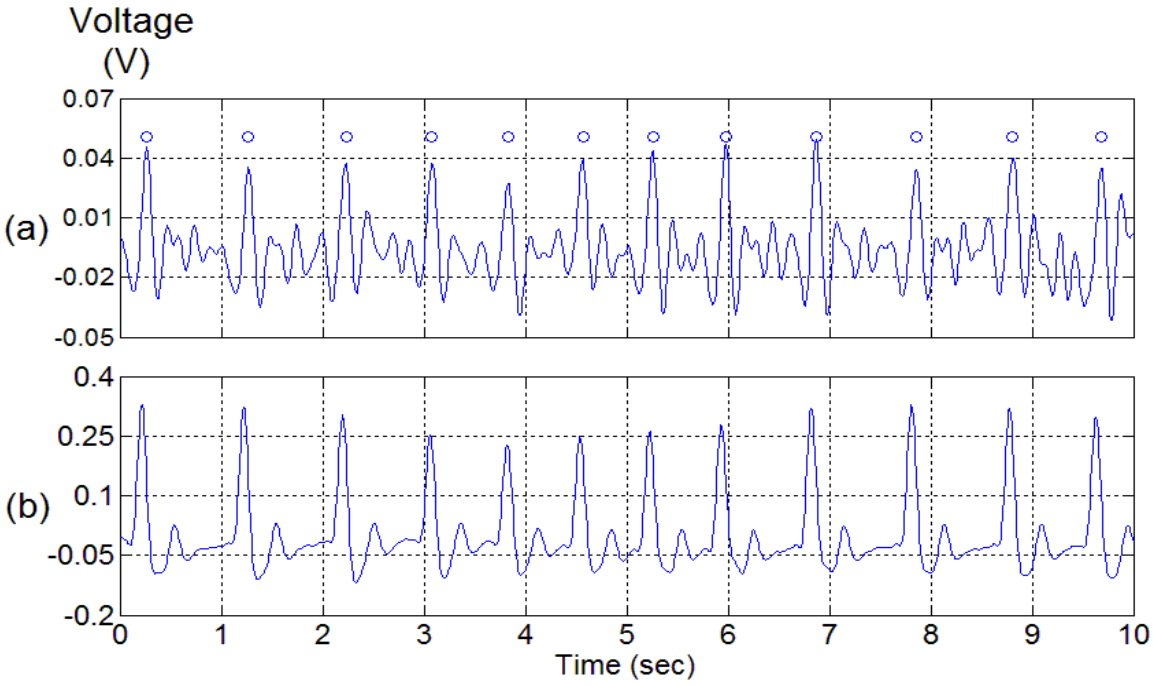




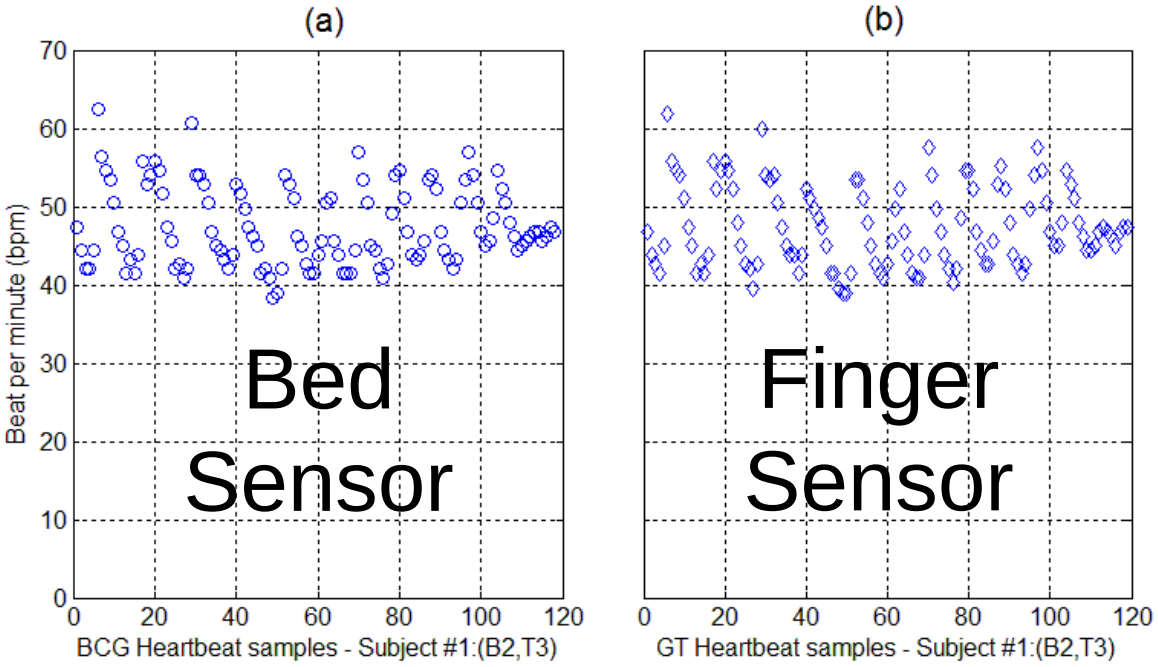
Heise et al., 2011, 2013

Heartbeats detected from bed sensor

Finger sensor



Beat to beat interval



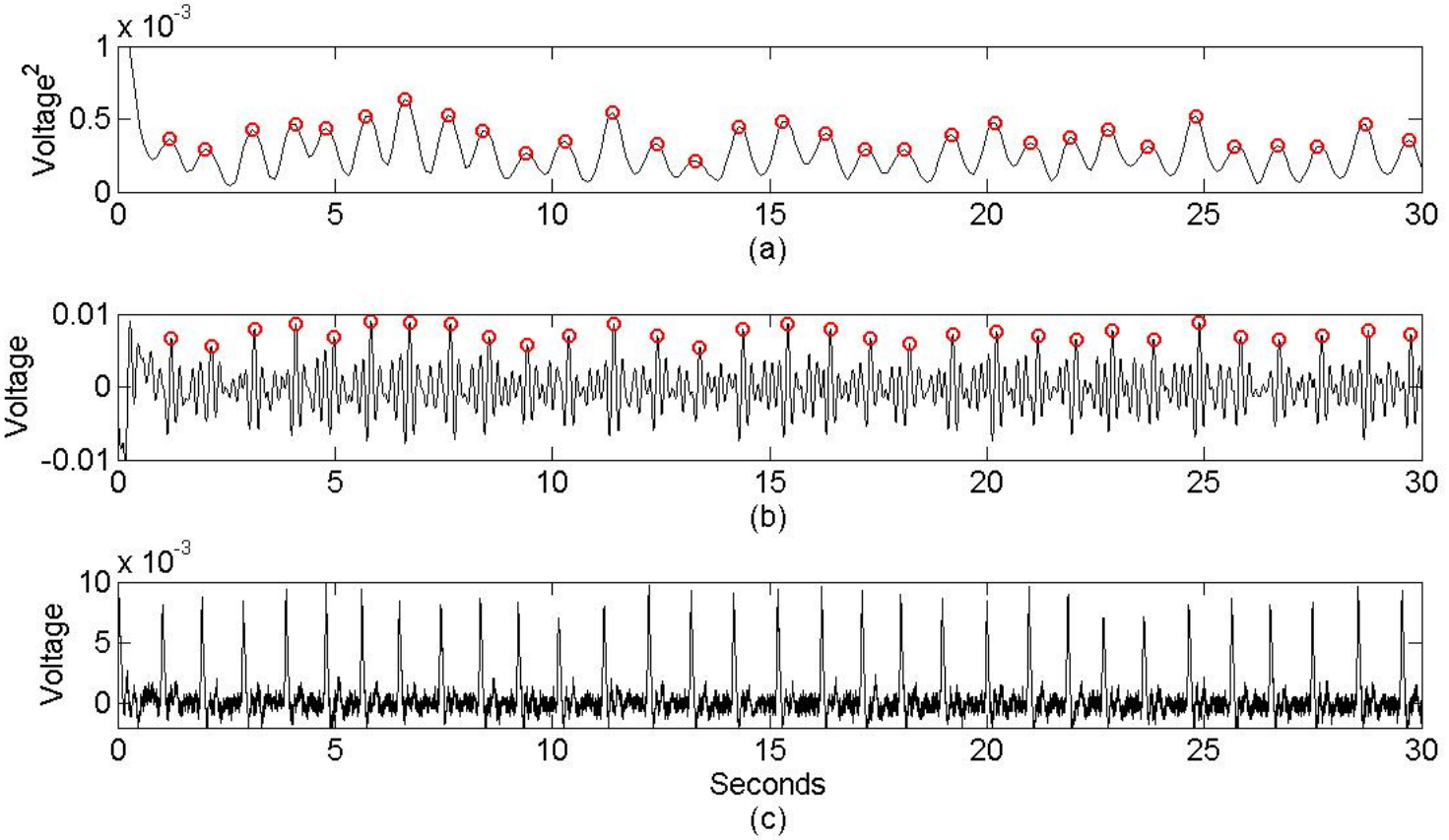
Rosales et al., 2012

New Algorithm : Computing Energy and locating the peaks

Energy Detection Results

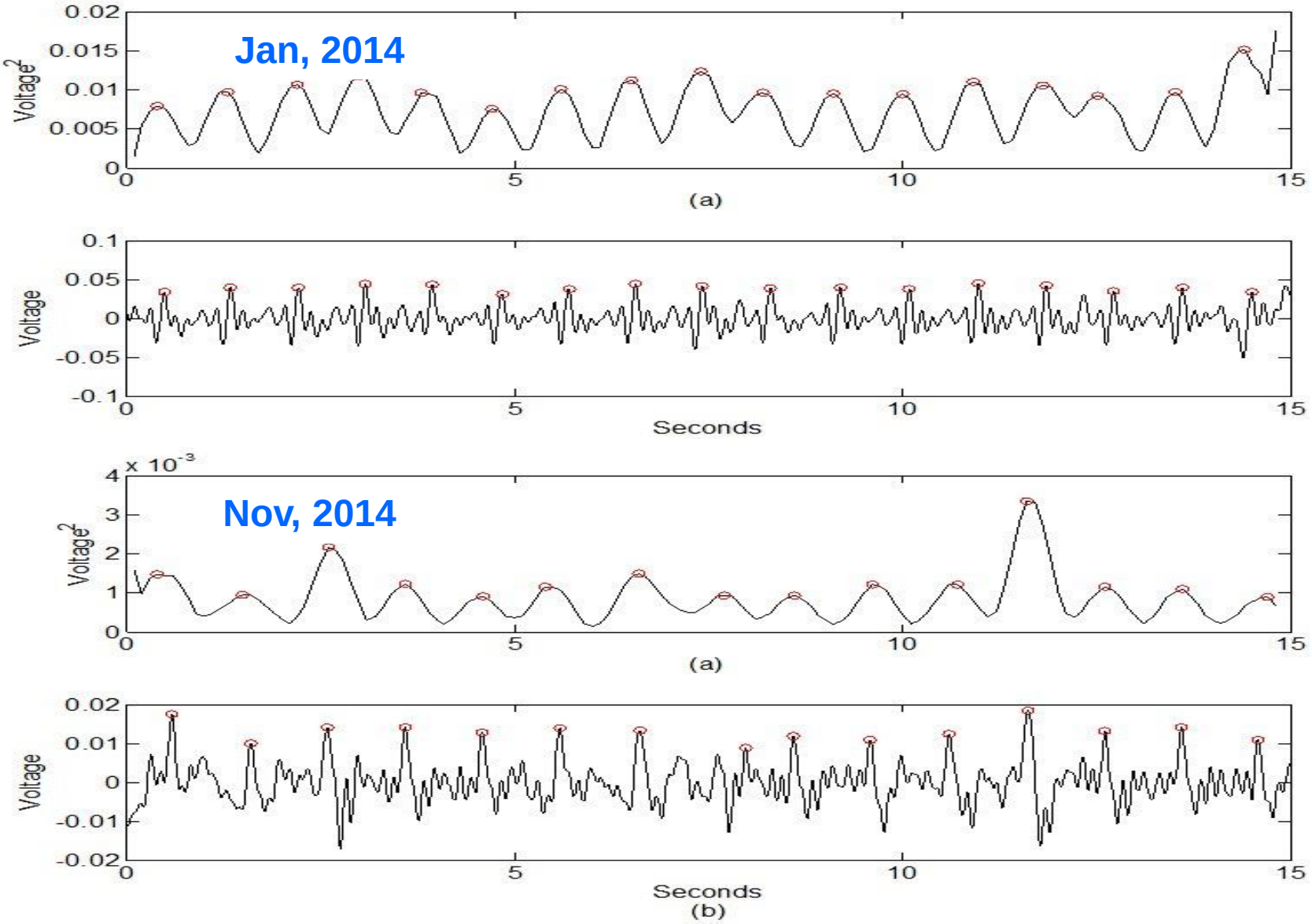
Peak Locations

Finger pulse

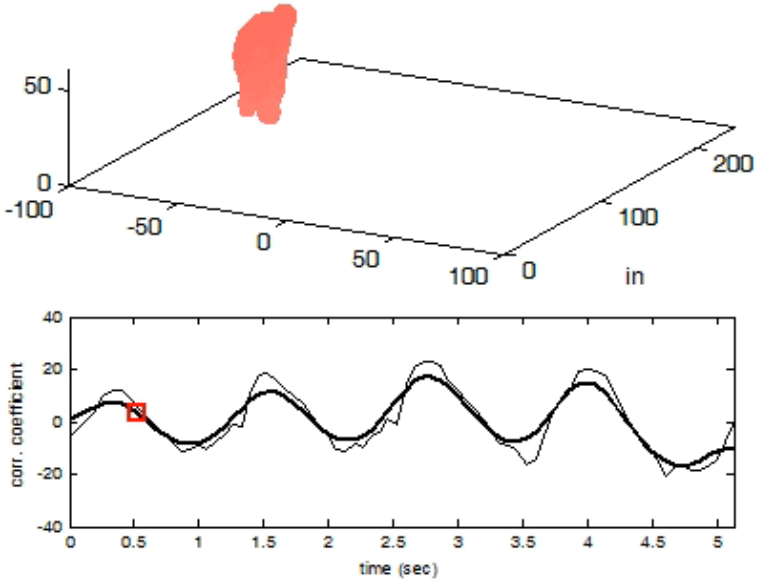


Lydon et al, EMBC 2015

Results : Older Adult from TigerPlace



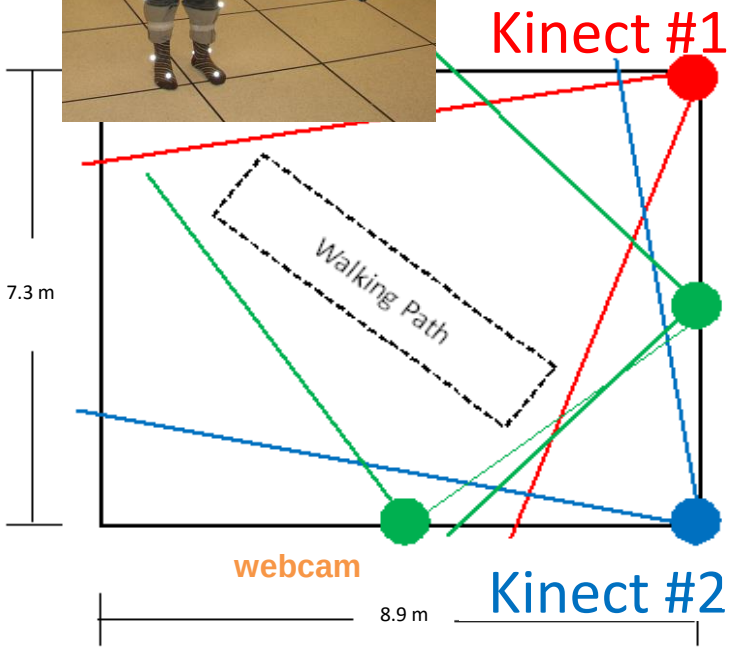
Capturing Gait in the Home Using Depth Images

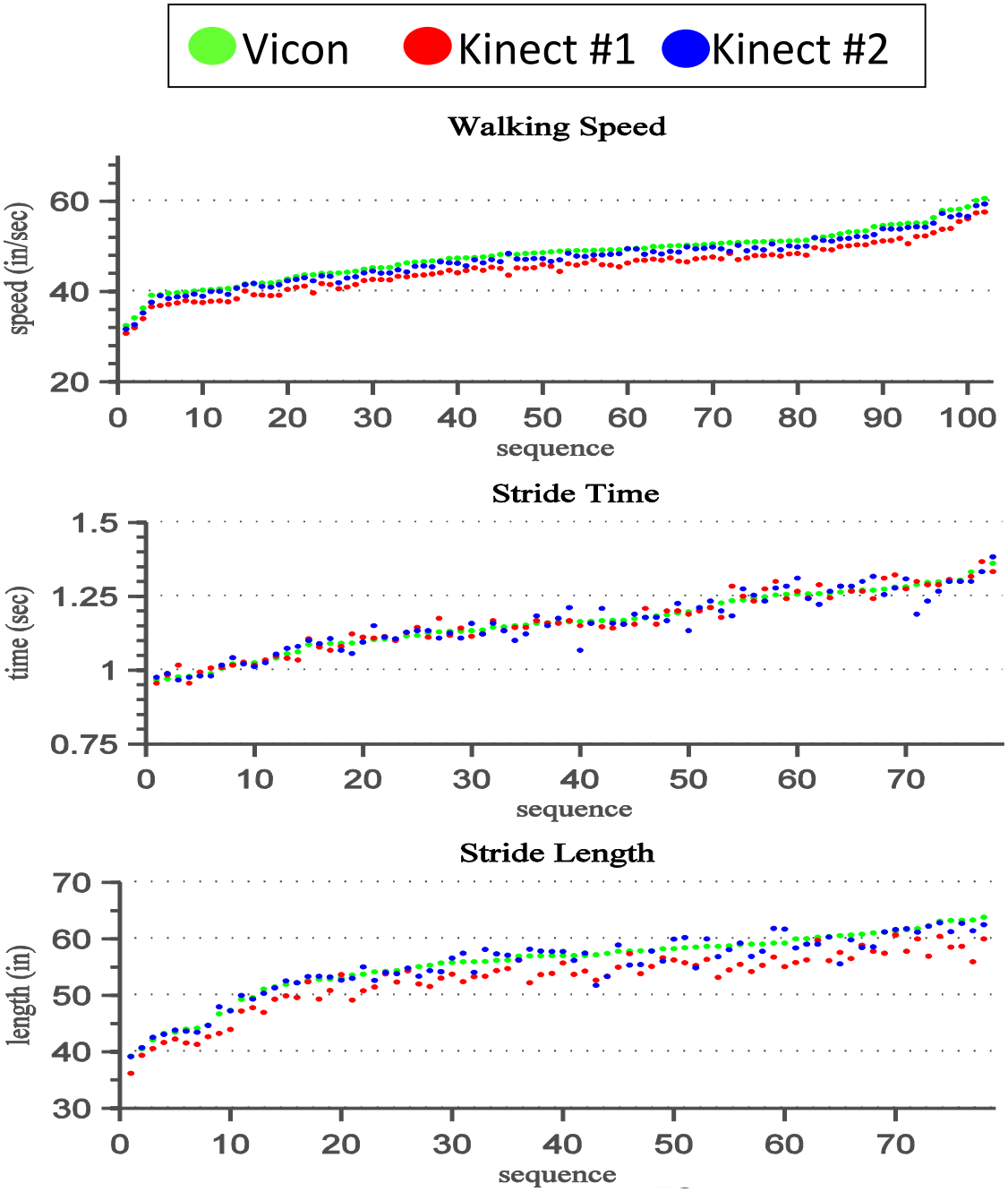


Stone & Skubic, *JAISE*, 2011, *TBE*, 2013

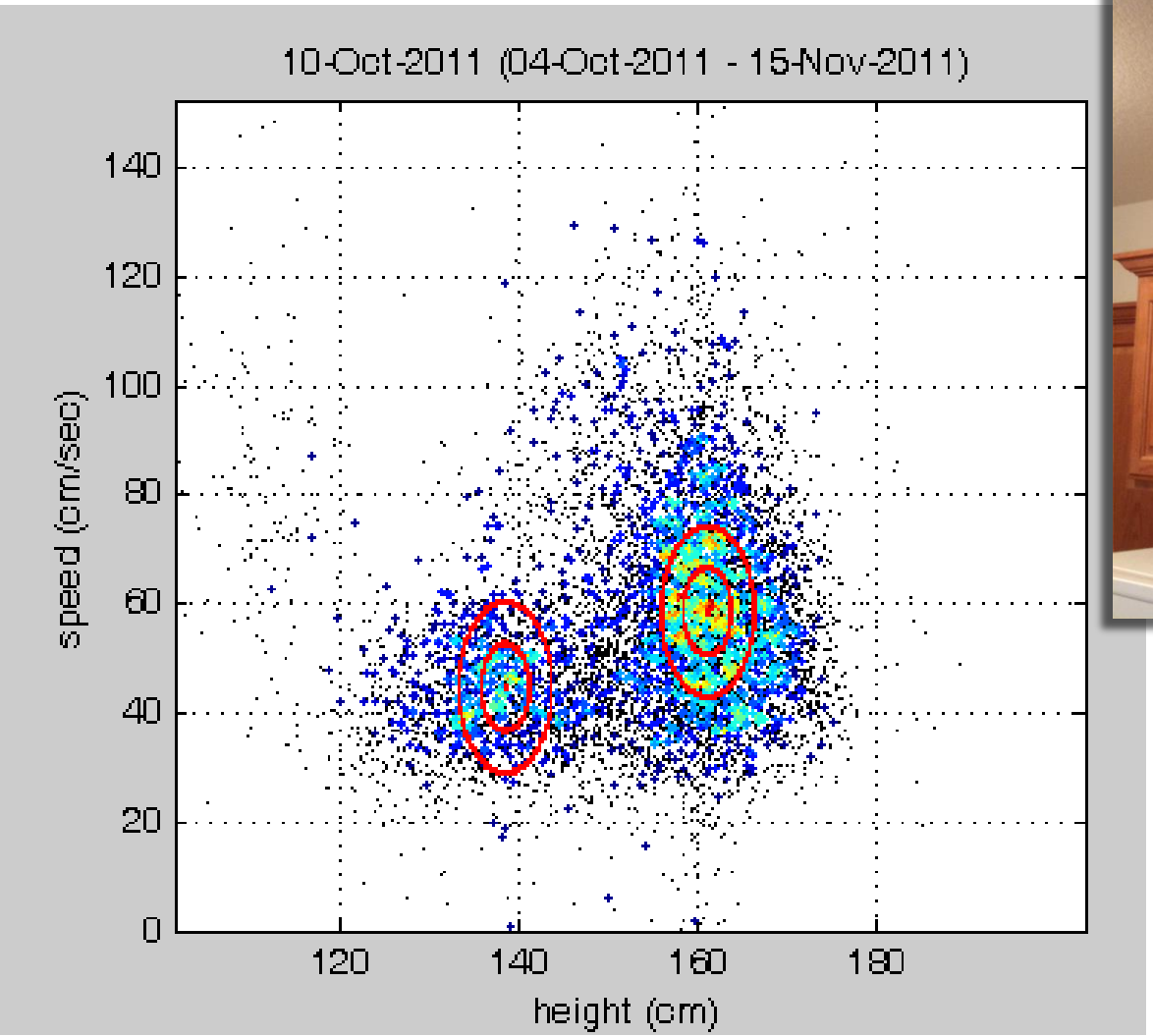
In-Home Gait: https://www.youtube.com/watch?v=MF6yZyLuuII

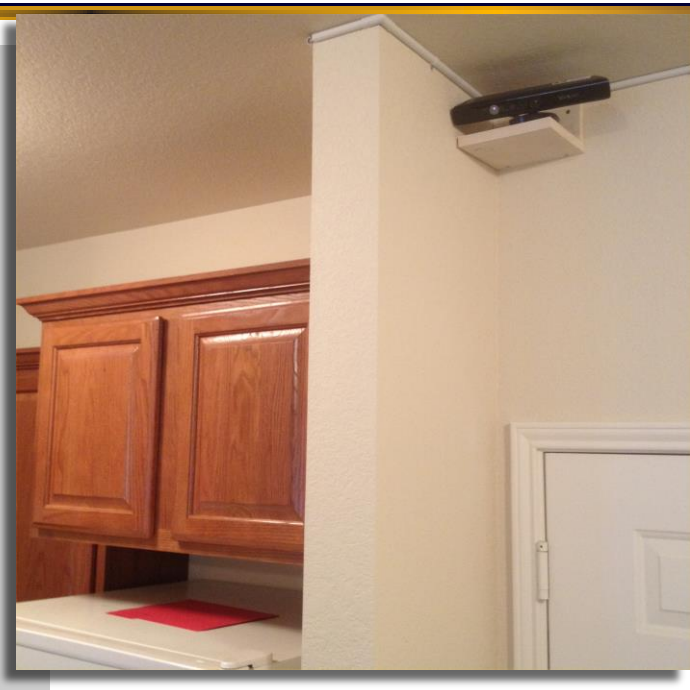
Validation in the Lab





Capturing Gait in the Home

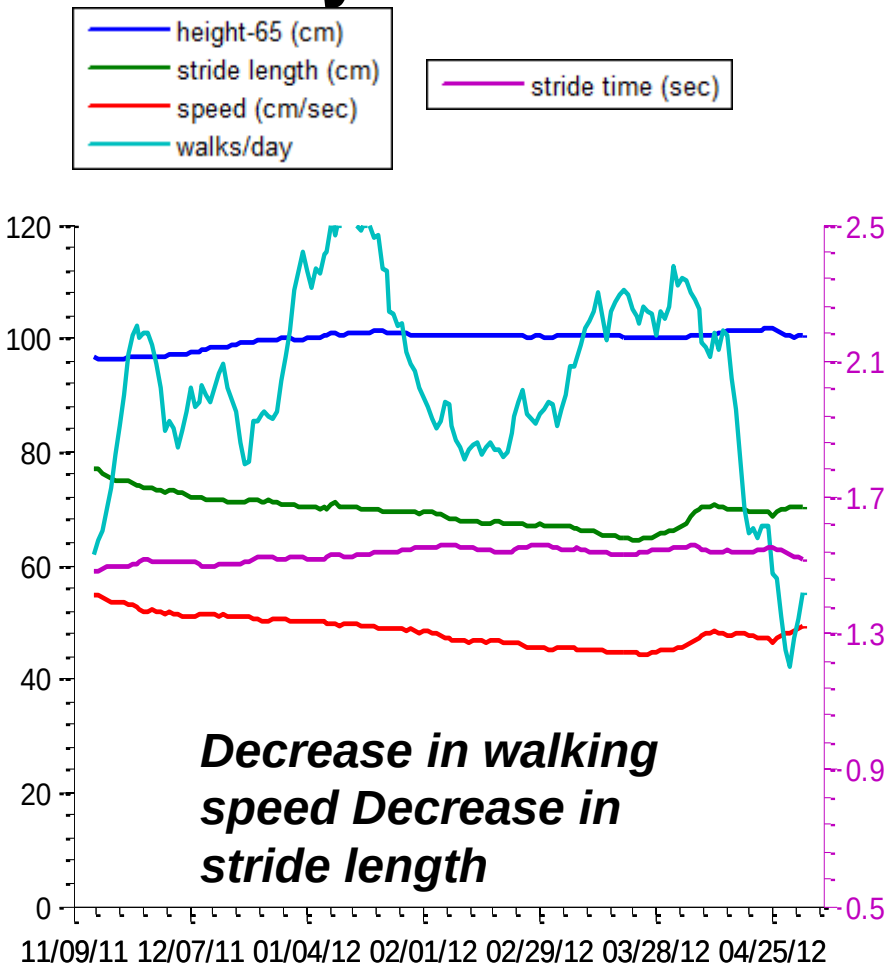




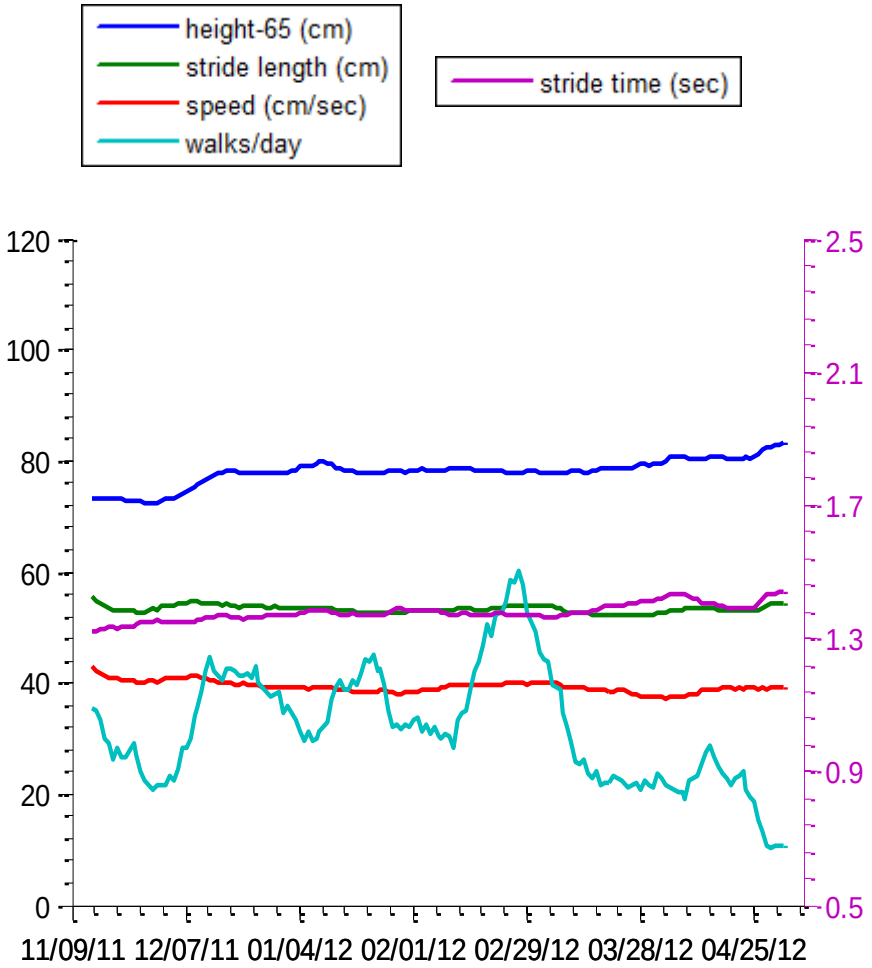
Stone & Skubic, EMBC 2012; *TBE* 2013; EMBC 2014.

Case Study: **Capturing Gait Changes**

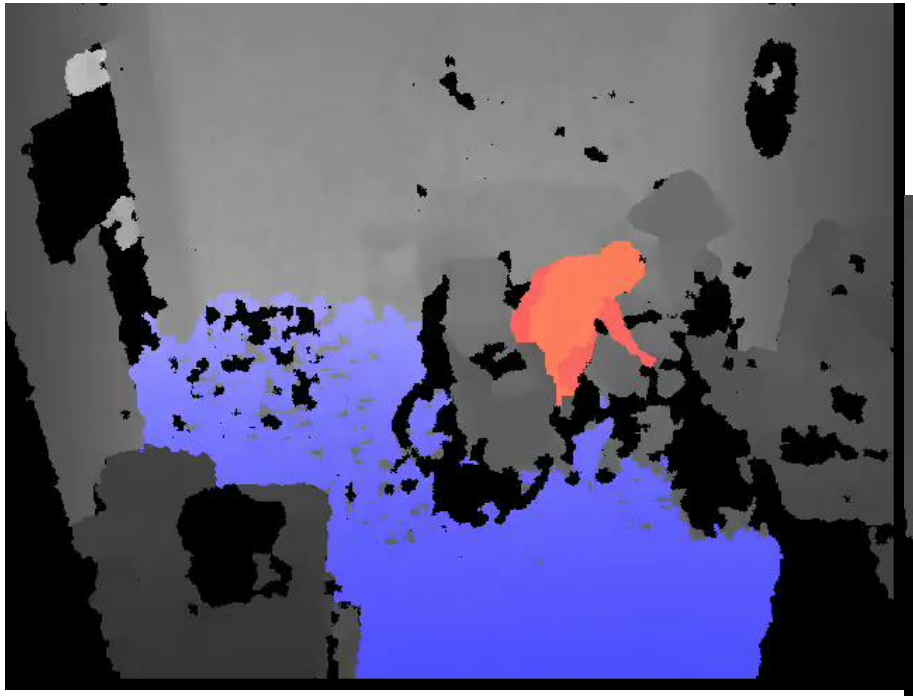
“Healthy” Husband

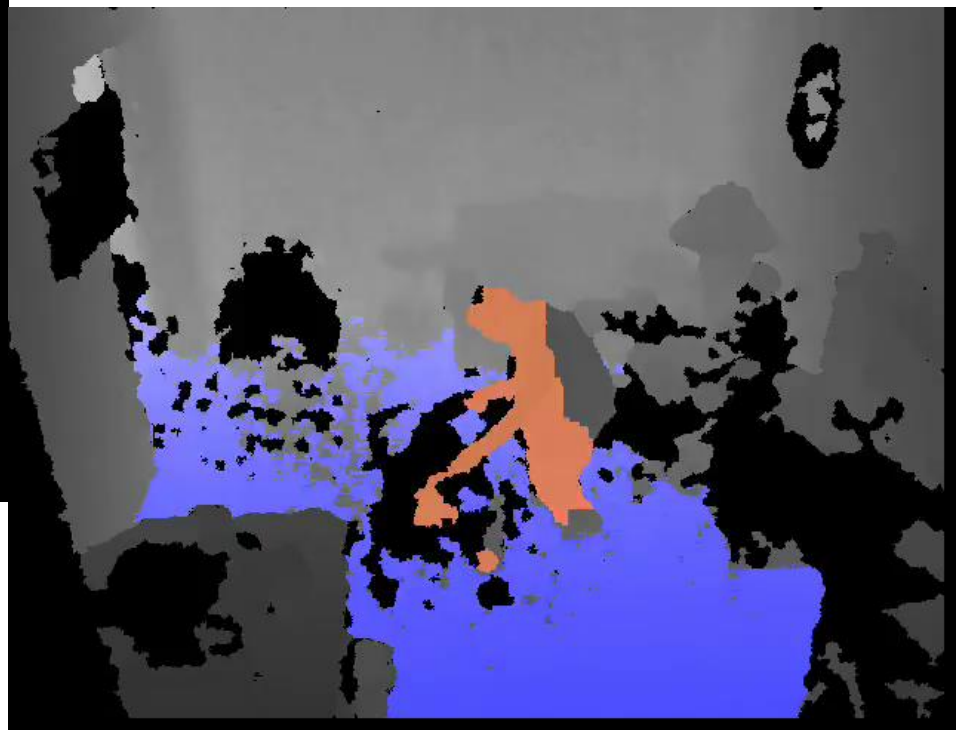


Wife with Parkinson’s



Capturing Falls in the Home with Depth Sensors

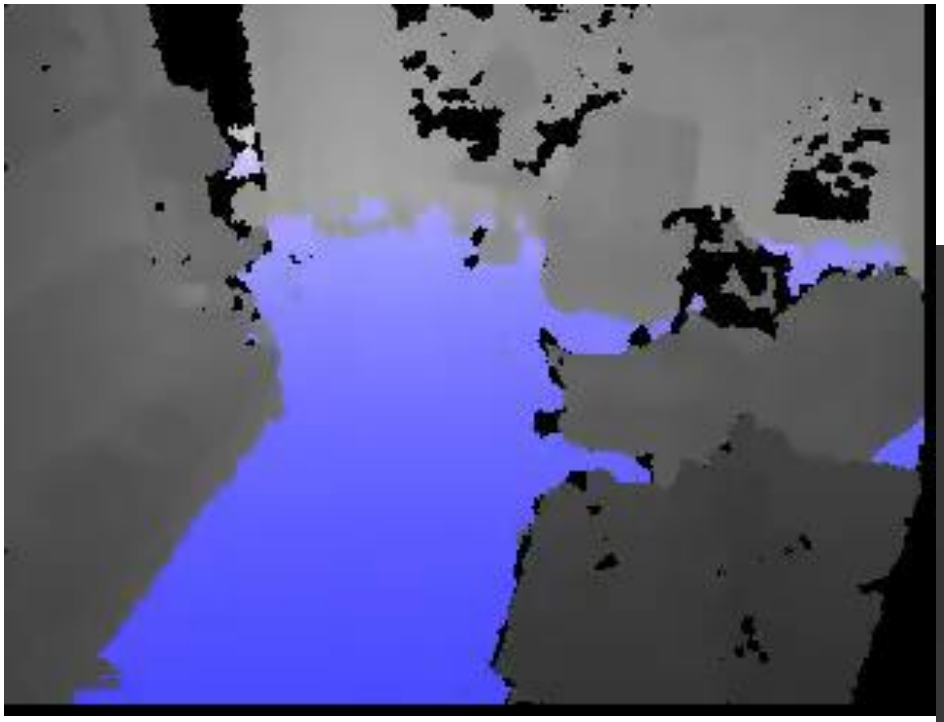


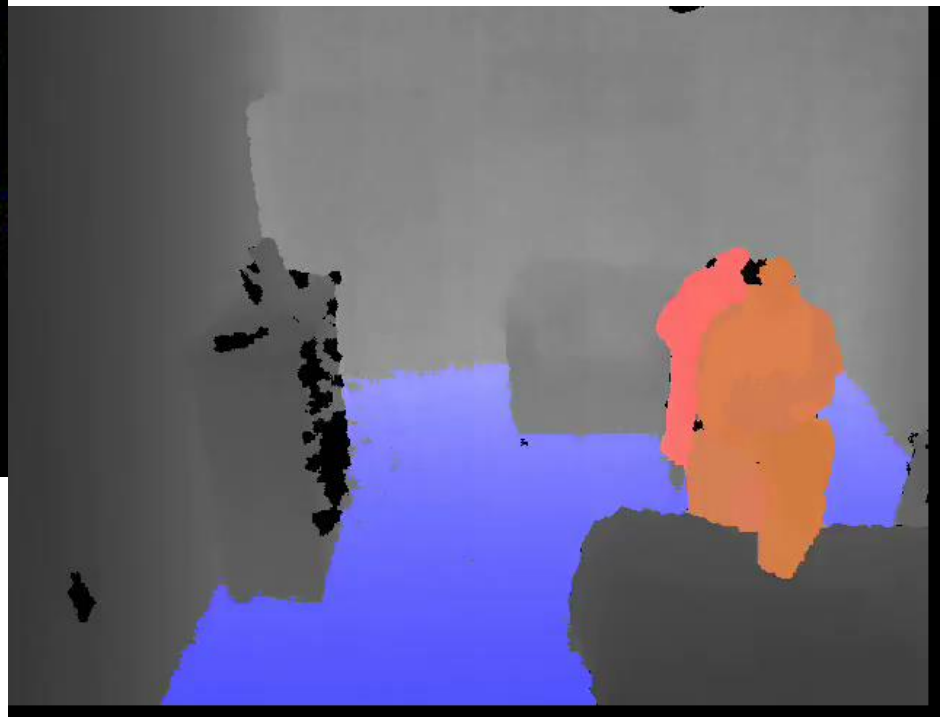


Stone & Skubic, 2014, 2015

In-Home Falls: https://www.youtube.com/watch?v=TFB7YOUmHho

False Alarms in the Home





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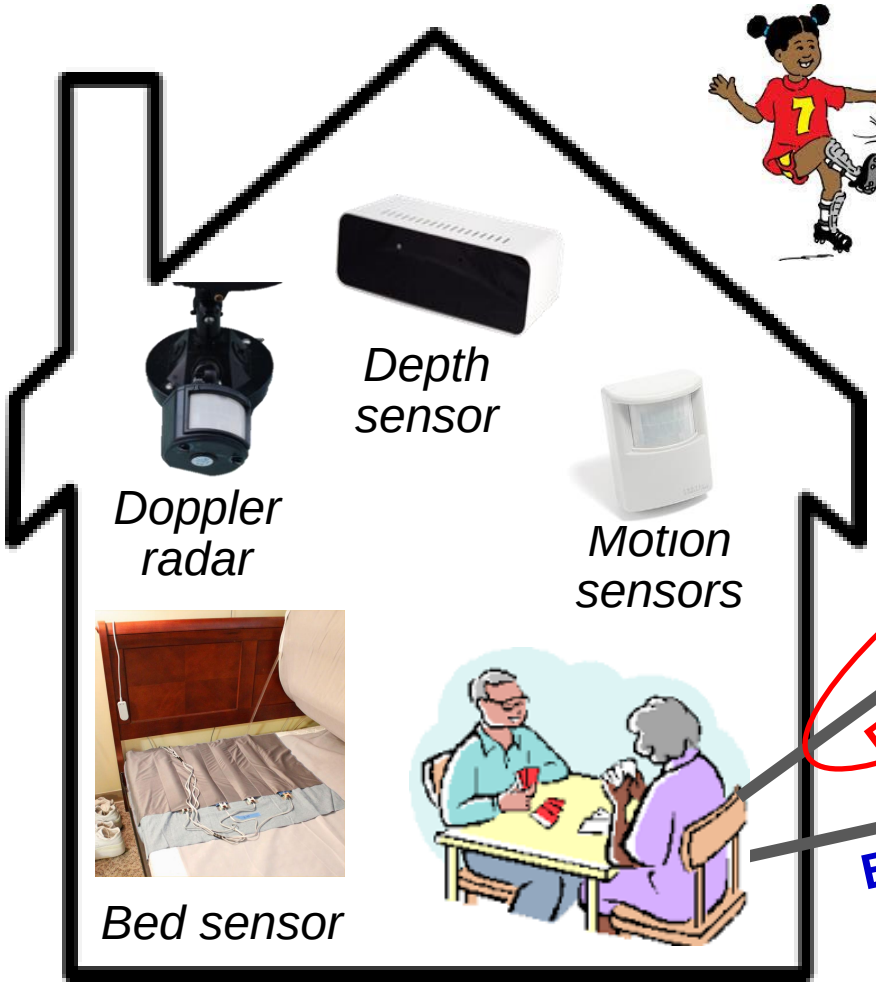

Doppler radar

Depth sensor

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Bed sensor

Kinect sensor

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Early illness detection

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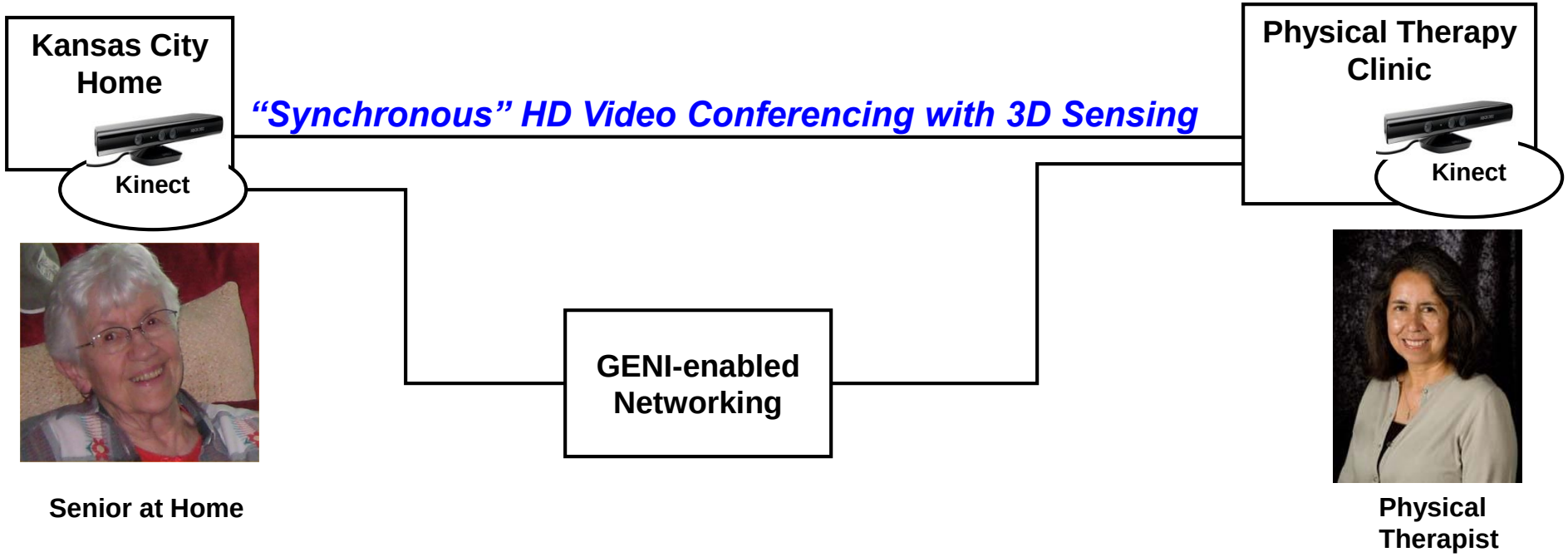
Remote Personalized Physical Therapy

In-Home Interface

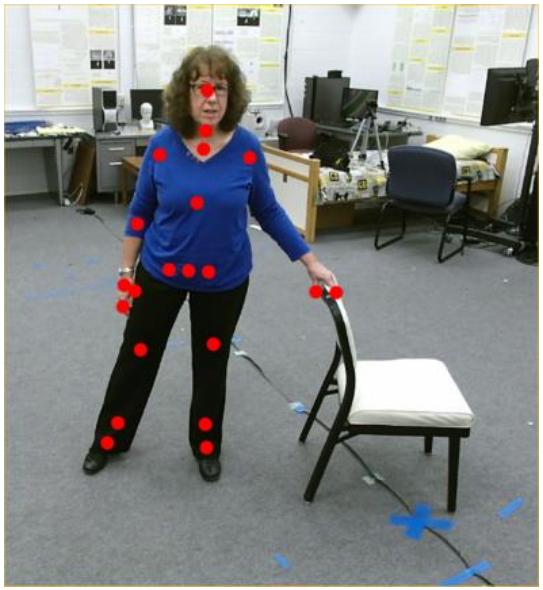
PT Interface



Calyam et al., 2015.

Microsoft Kinect

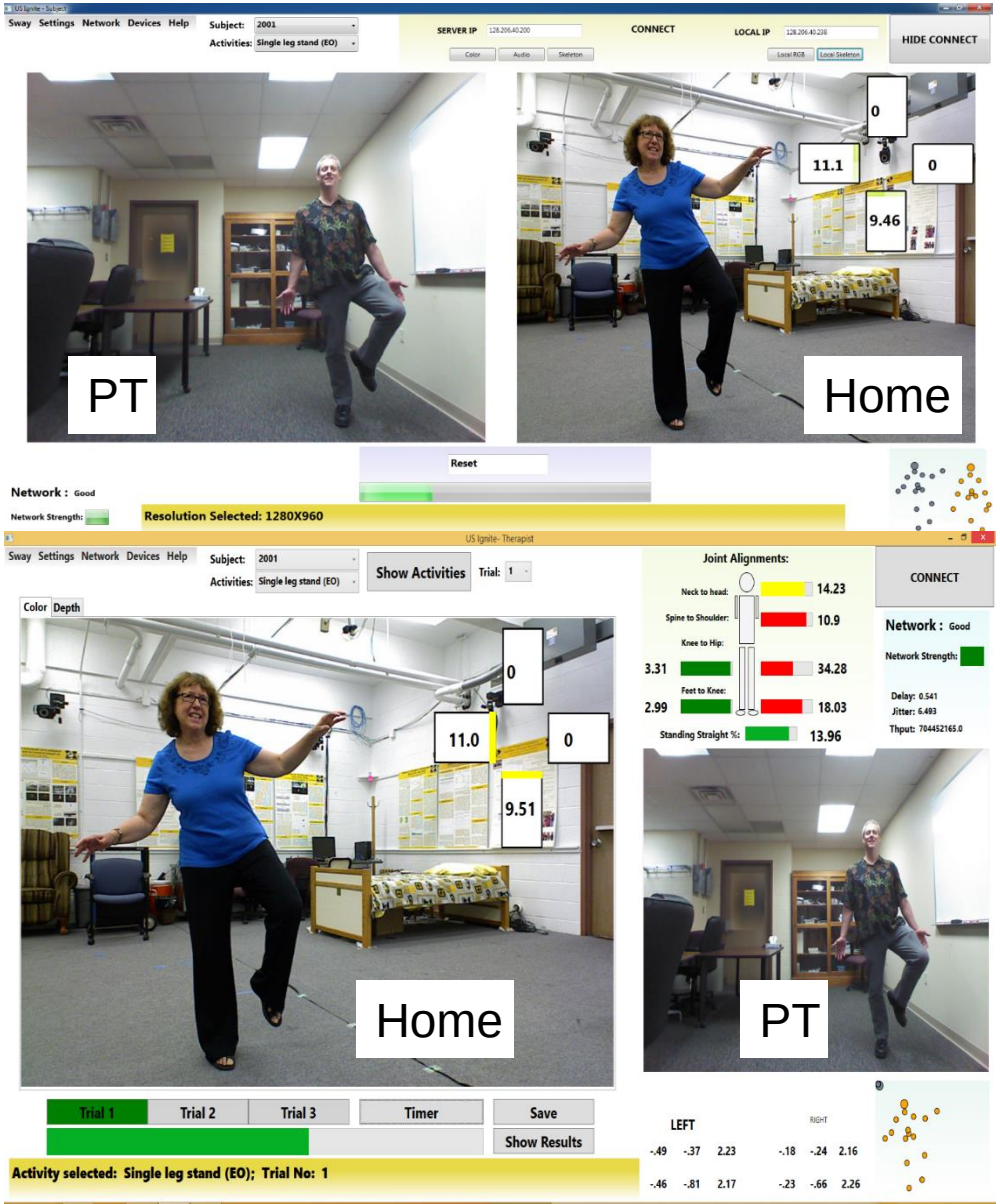
- Color camera
- Depth camera
- Microphones



Color Camera	**1920 x 1080 @ 30 fps**
Depth Camera	**512 x 424**
Max Depth Distance	**~4.5 m**
Min Depth Distance	**50 cm**
Horizontal Field of View	**70 degrees**
Vertical Field of View	**60 degrees**
Skeleton Model	**26 joints**
Skeletons Tracked	**6**

Remote Physical Therapy – from clinic to home

- More than video conferencing; Includes 3D sensing



In-home "patient" view

Physical therapist view
Controlled by voice commands

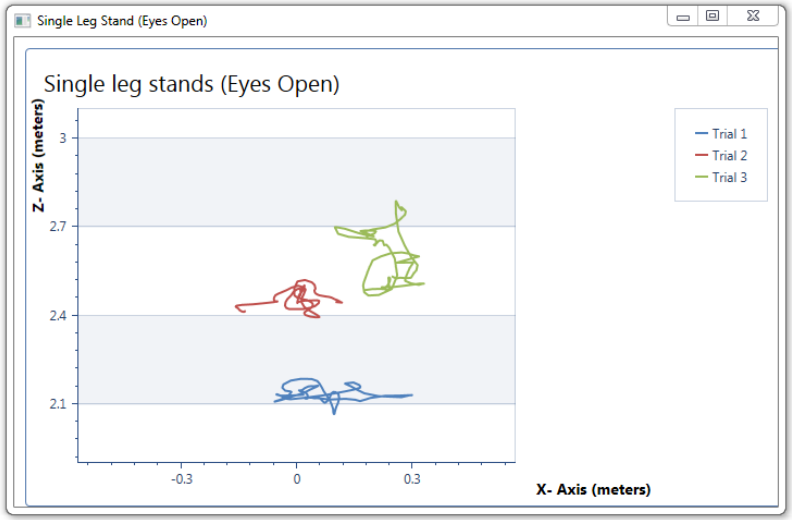
Mishra et al., 2015

PT side

Results

< Back

RESULTS



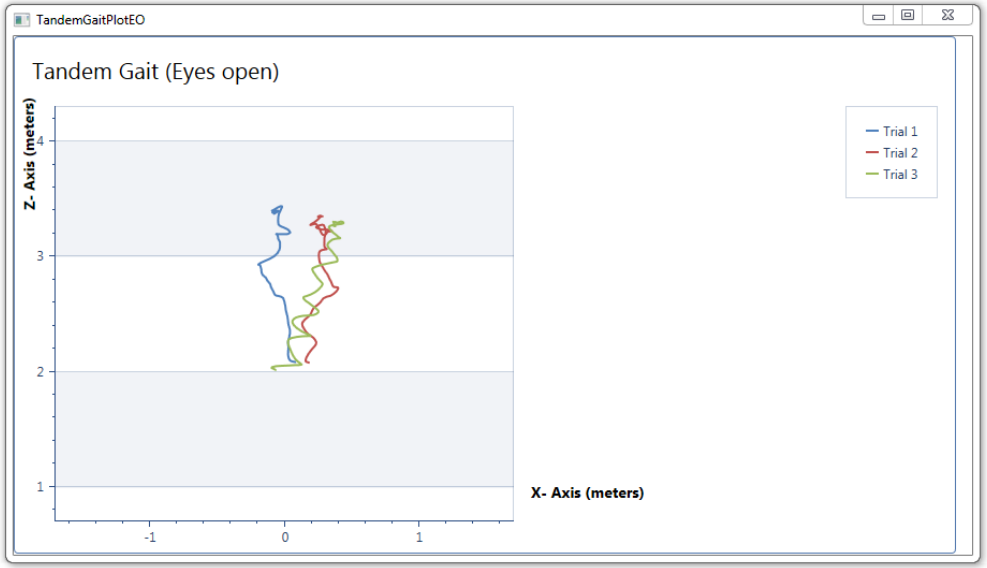
Single leg stand (EO)

	Trial 1	Trial 2	Trial 3
Max Sway Front: (deg)	20.05	13.87	51.28
Max Back Sway: (deg)	6.17	7.2	31.4
Max Right Sway: (deg)	21.39	5.27	24.85
Max Left Sway: (deg)	47.95	15.21	50.13
Total time performed:(out of 20 secs) (sec)	19.55	16.74	15.37

Results

< Back

RESULTS



Tandem Gait (EO)

	Trial 1	Trial 2	Trial 3
Max Sway Front: (deg)	6.81	14.99	15.34
Max Back Sway: (deg)	4.36	3.31	1.68
Max Right Sway: (deg)	26.42	7.66	4.24
Max Left Sway: (deg)	11.32	19.36	17.58

Mishra et al., 2015

Eldertech Collaborators



















Nursing



Social Work
CS/Engineering



Family Medicine

HMI

Physical Therapy

Education

Foresite Healthcare

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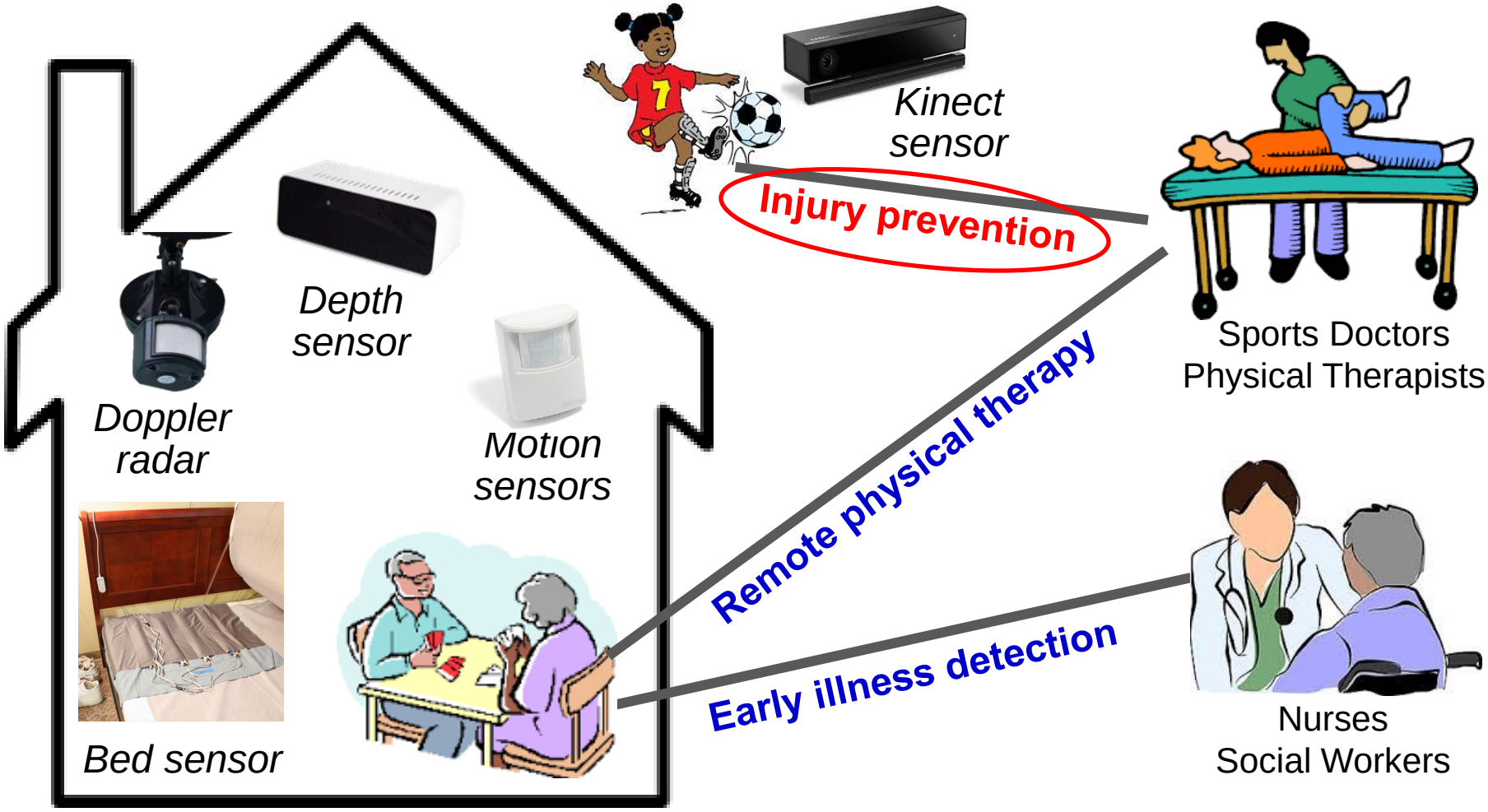
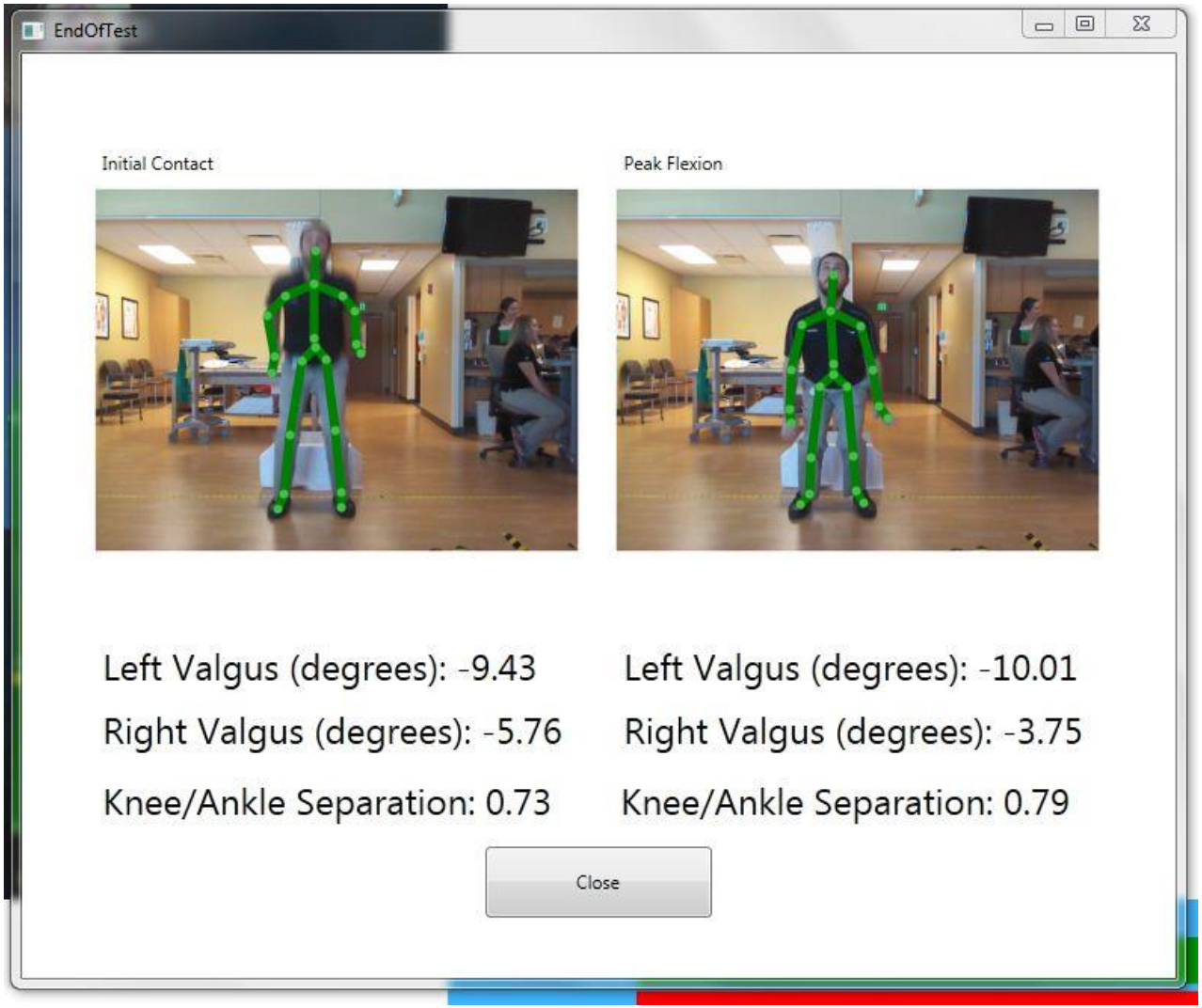


Assessing for ACL Injury Risk

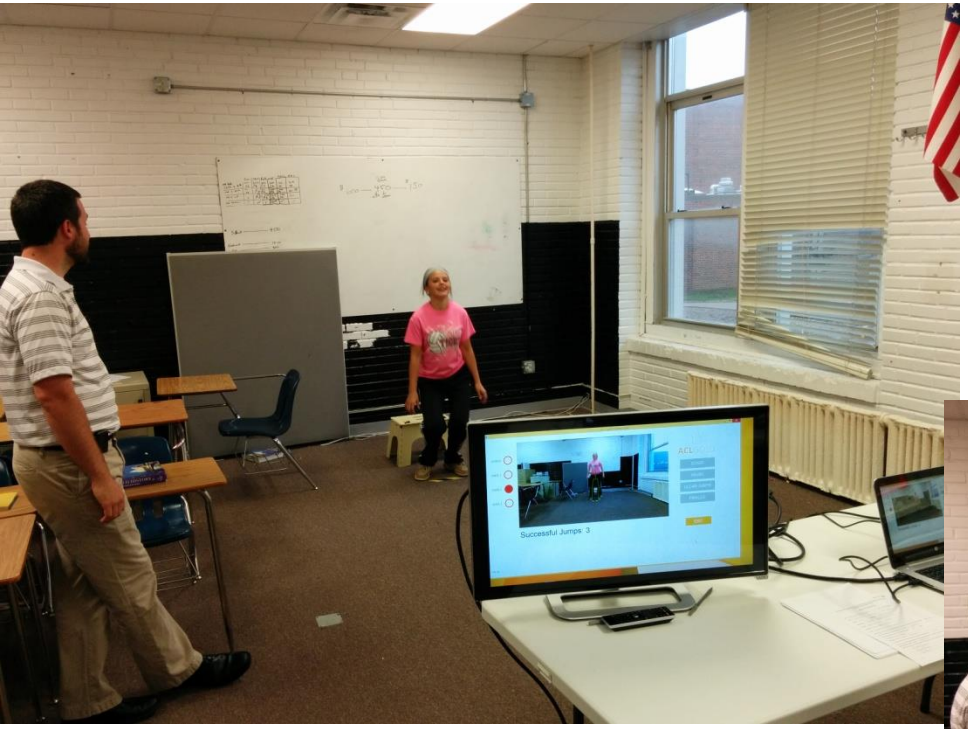
Rachel Coward/MU Publications

Portable Screening Tool

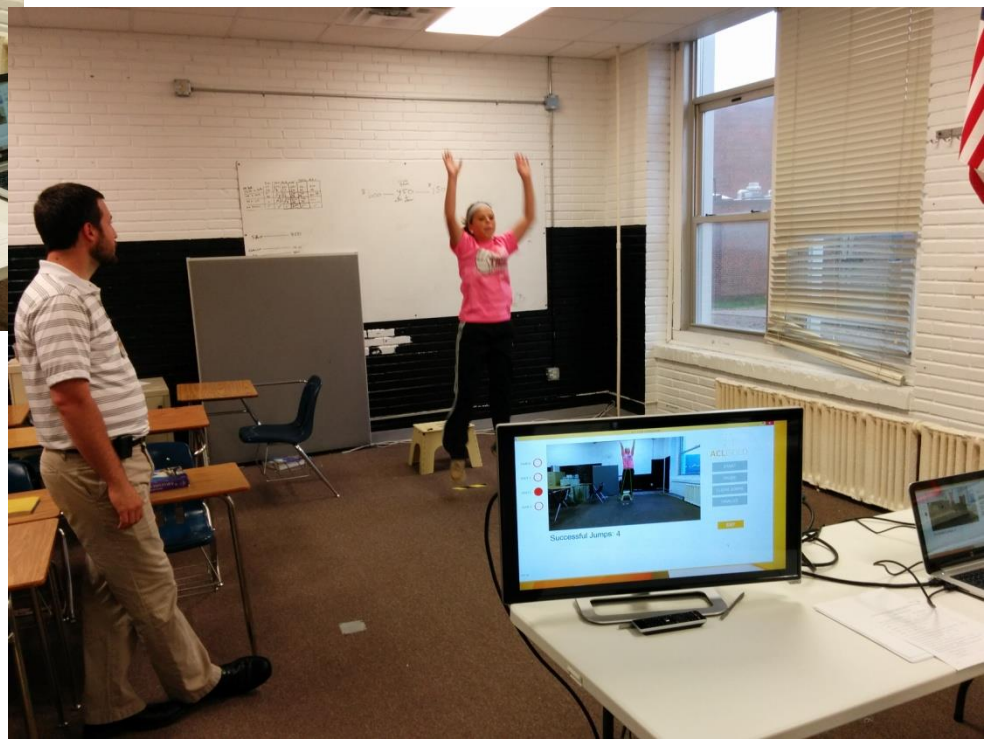


Stone, Butler, McRuer, Gray, Marks & Skubic, 2013

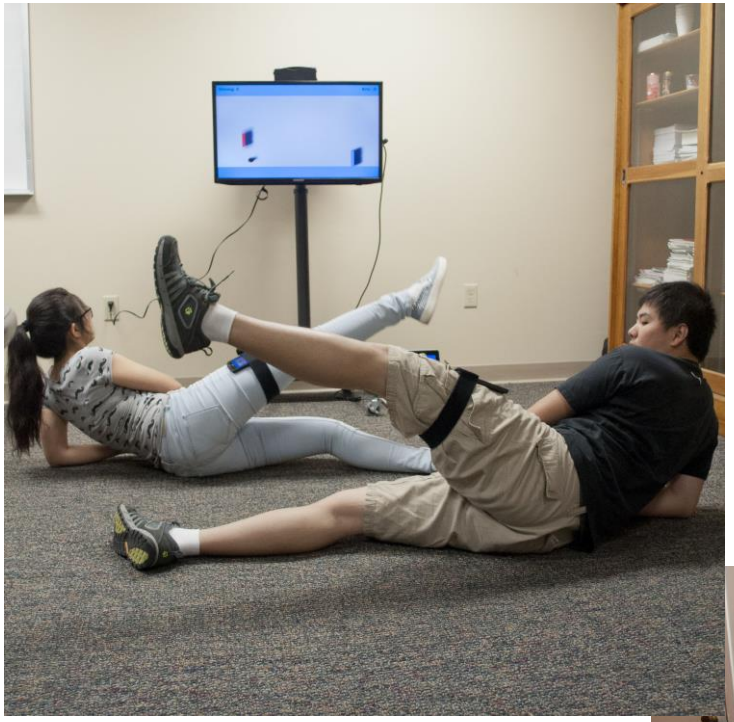
Screening in Area High Schools

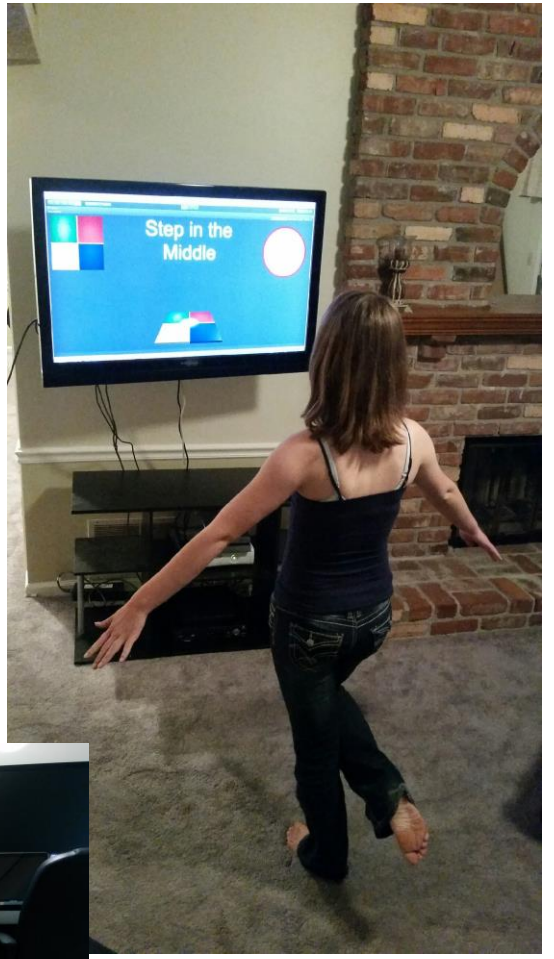


168 high school athletes



Exergame Prototypes

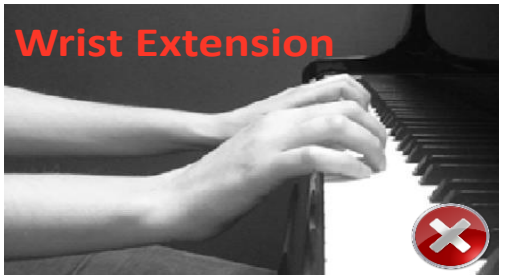




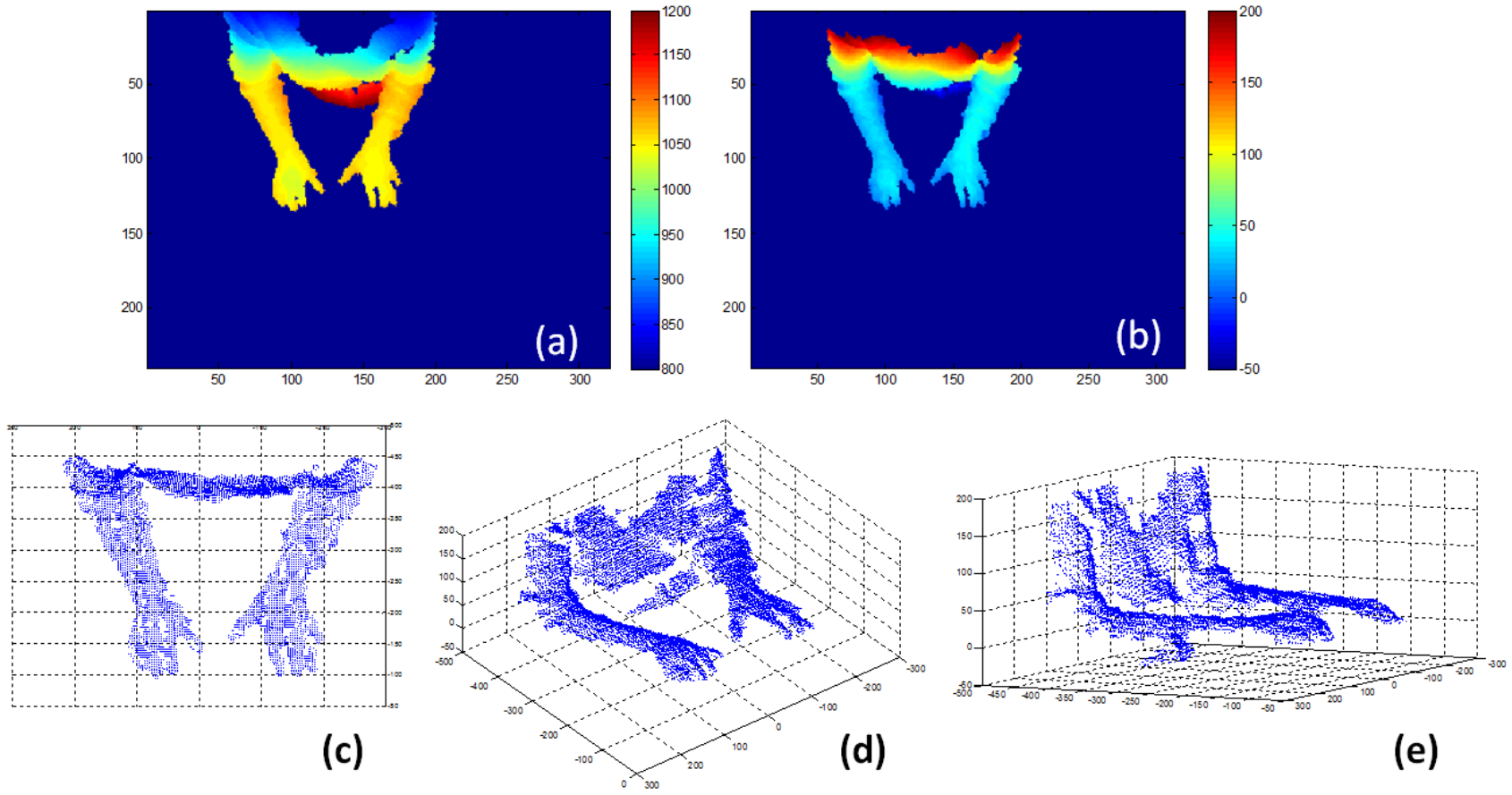
Huo et al., 2015

Recognizing Harmful Hand Postures

Savvidou, Li, Willis & Skubic, 2015



Hands are tracked & assessed in depth videos using the Kinect



Li, Savvidou, Willis & Skubic, 2014

Prehab/Rehab Collaborators

CS/Engineering

Medicine

Music

Social Work

Physical Therapy

Occupational Therapy

Our Goal: Healthy Living at Any Age

www.eldertech.missouri.edu