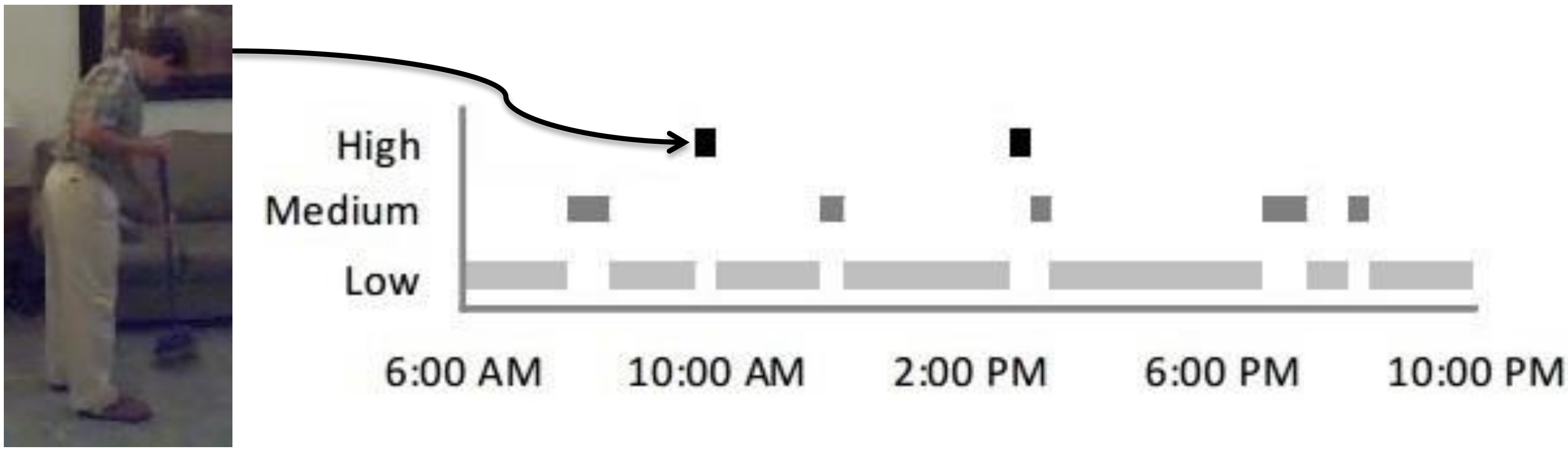
Estimating Daily Energy Expenditure from Video for Assistive Monitoring



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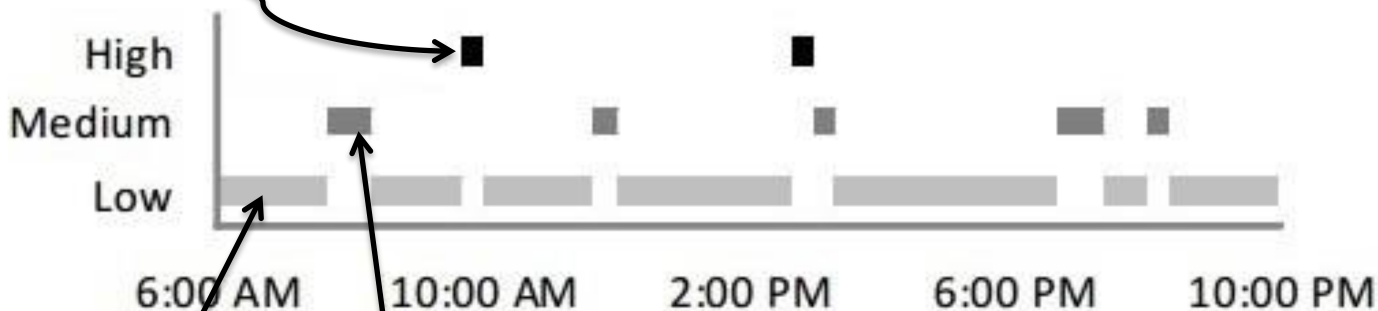
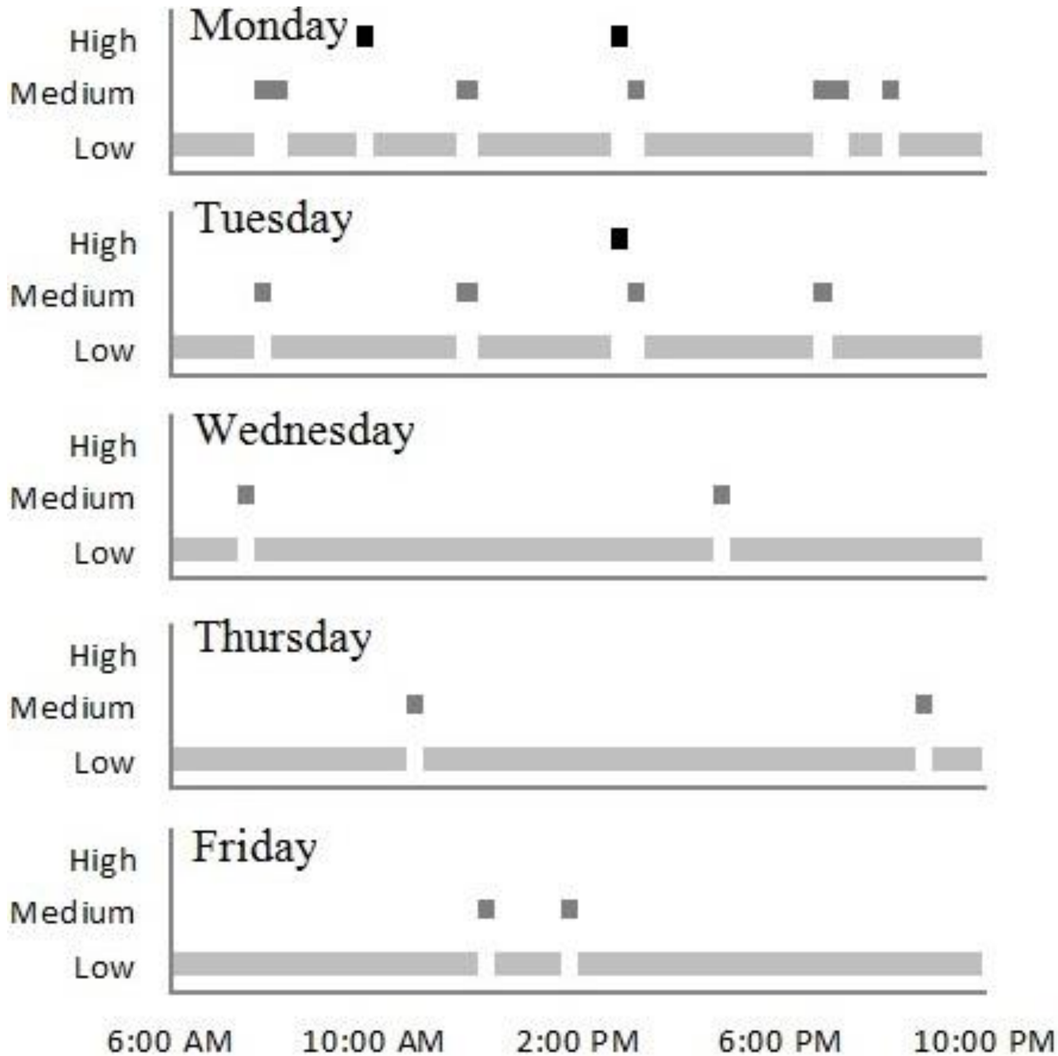
Daily energy expenditure graph

Energy expenditure levels on Monday



Estimated energy expenditure	Energy exp. level
< 3 Calories/minute	Low
Other	Medium
> 6 Calories/minute	High

Daily energy expenditure example



Reasons to estimate energy expenditure of elderly

- Detect trends
- Motivate more activity[1]
- Sufficient activity associations:

Mortality risk[2]
Onset of dementia[3]
Likelihood of falls[4]

Emotional well-being[5]

[1] Courneya, et al. Relationships Among the Theory of Planning Behavior, Stages on Change, and Exercise Behavior in Older persons over a Three Year Period.
[2] Hirvensalo, et al. Mobility Difficulties and Physical Activity as Predictors of Mortality and loss of Independence in the Community-Living Older Population.
[3] Buchman , et al.. Total Daily Physical Activity and the Risk of AD and cognitive Decline in Older Adults.
[4] Lord , et al. The Effect of a 12-Month Exercise Trial on Balance, Strength, and Falls in Older Women: A Randomized Controlled Trial.
[5] Fox, K.R. The Influence of Physical Activity on Mental Well-Being.

Commercial energy estimation methods

Respiratory chamber

Direct calculation

$1,000,000 USD

Photo credit: T. Ortega Gaines/ Charlotte Observer/MCT

Doubly-labeled water (DLW)

Best indirect

$30,000 USD

Photo credit: cosmedusa.com

BodyBugg

Common

$150 USD

Academic energy estimation methods

Accelerometers[6]
(30 years of work)

Body-worn camera[7]

Photo credit: Yao[7]

[6] Zhang, et al. Improving Energy Expenditure Estimation for Physical Activity.
[7] Yao, et al. A Video Processing Approach to the Study of Obesity.

Activity recognition + Conversion chart

Body-worn[8]

Photo credit: Choudhury[3]

Off-body[9,10]

Photo credit: Tapia[2]

+

Conversion chart[11]

Activity (1hr duration)	Calories burnt by 160 lbs person
2 mph walk	204
3.5 mph walk	314
Light aerobics	365
…	…

[8] Choudhury, et al. The Mobile Sensing Platform: An Embedded Activity Recog. System.
[9] Tapia, et al. Activity Recognition in the Home Using Simple and Ubiquitous Sensors.
[10] Zhou, et al. Activity Analysis, Sum., and Vis. for Indoor Human Activity Monitoring.
[11] Mayo Clinic. http://www.mayoclinic.com/health/exercise/SM00109

Simpler method advantages over activity recognition + conversion chart

Lightweight processing

Operate on low quality or blurred

Reasons to estimate energy expenditure with video

Body-worn

Pro: Anywhere

Con: Not always worn

Detect other events

Privacy enhance-able

Estimate daily energy expenditure from one camera in 2 steps

Step 1

Step 2

Camera video

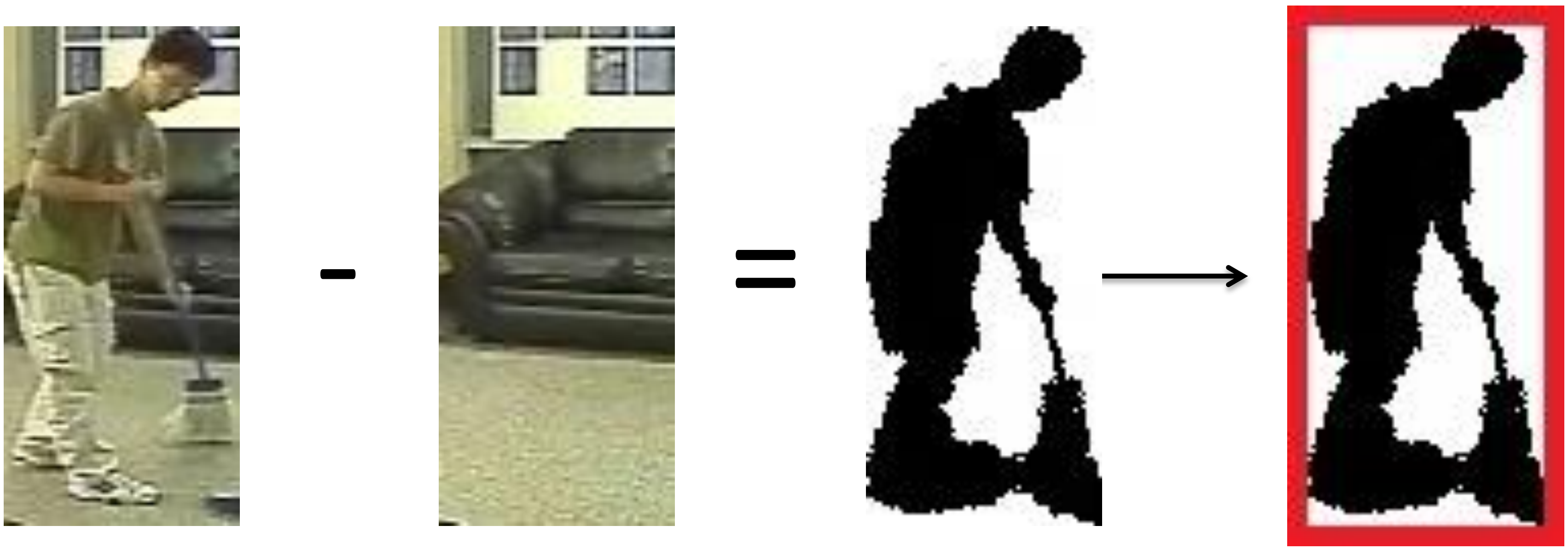
Extract Minimum Bounding Rectangle (MBR) around person

Convert MBR into energy expenditure estimation

1,865 Calories on Monday

Step 1: Person tracking and MBR extraction

via foreground-background segmentation (details in paper)



Video frame — Background image = Foreground → Minimum bounding rectangle (MBR)

Step 2: Convert MBR to daily energy expenditure estimation

- Extract feature F from each frame of video's MBR

F = (e.g.) Height

- Standardize feature data at time i $S_i = \dfrac{F_i - \mu_F}{\sigma_F}$

- Sum the absolute differences between successive standardized data

$$sum = \sum_{i=2}^{n} |S_i - S_{i-1}|$$

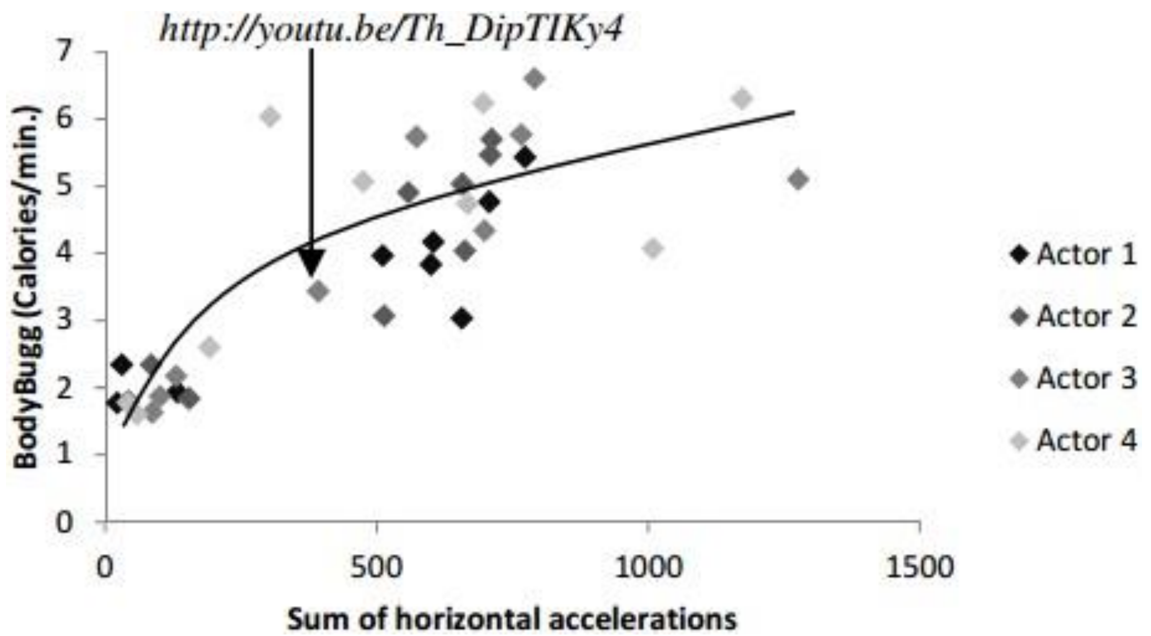
- Regression to convert sum to Calories $Calories = R(sum)$

Best MBR feature for energy estimation

MBR feature (sum)	Correlation w/ BodyBugg	P-value
Height	$r = 0.45$	$p < 0.01$
Width	$r = 0.72$	$p < 0.01$
Vertical velocity	$r = 0.72$	$p < 0.01$
Horizontal velocity	$r = 0.77$	$p < 0.01$
Combined velocities	$r = 0.77$	$p < 0.01$
Vertical acceleration	$r = 0.70$	$p < 0.01$
Horizontal acceleration	**$r = 0.80$**	**$p < 0.01$**
Combined acceleration	$r = 0.79$	$p < 0.01$
Horizontal work	$r = -0.16$	$p = 0.84$
Vertical work	$r = -0.23$	$p = 0.92$
Combined work	$r = -0.22$	$p = 0.91$
[Motion in video]	*$r = -0.01$*	*$p = 0.53$*

Best regression model for energy estimation

Regression model	R^2 – value
Power	**0.76**
Exponential	0.69
Logarithmic	0.67
Linear	0.64



Recordings gathered

- Mock in-home environment
- Four actors performing 9 activities for 30 minutes each (18 hours of recordings)
- Video from popular in-home camera kit
- BodyBugg ($150) for Calorie expenditure

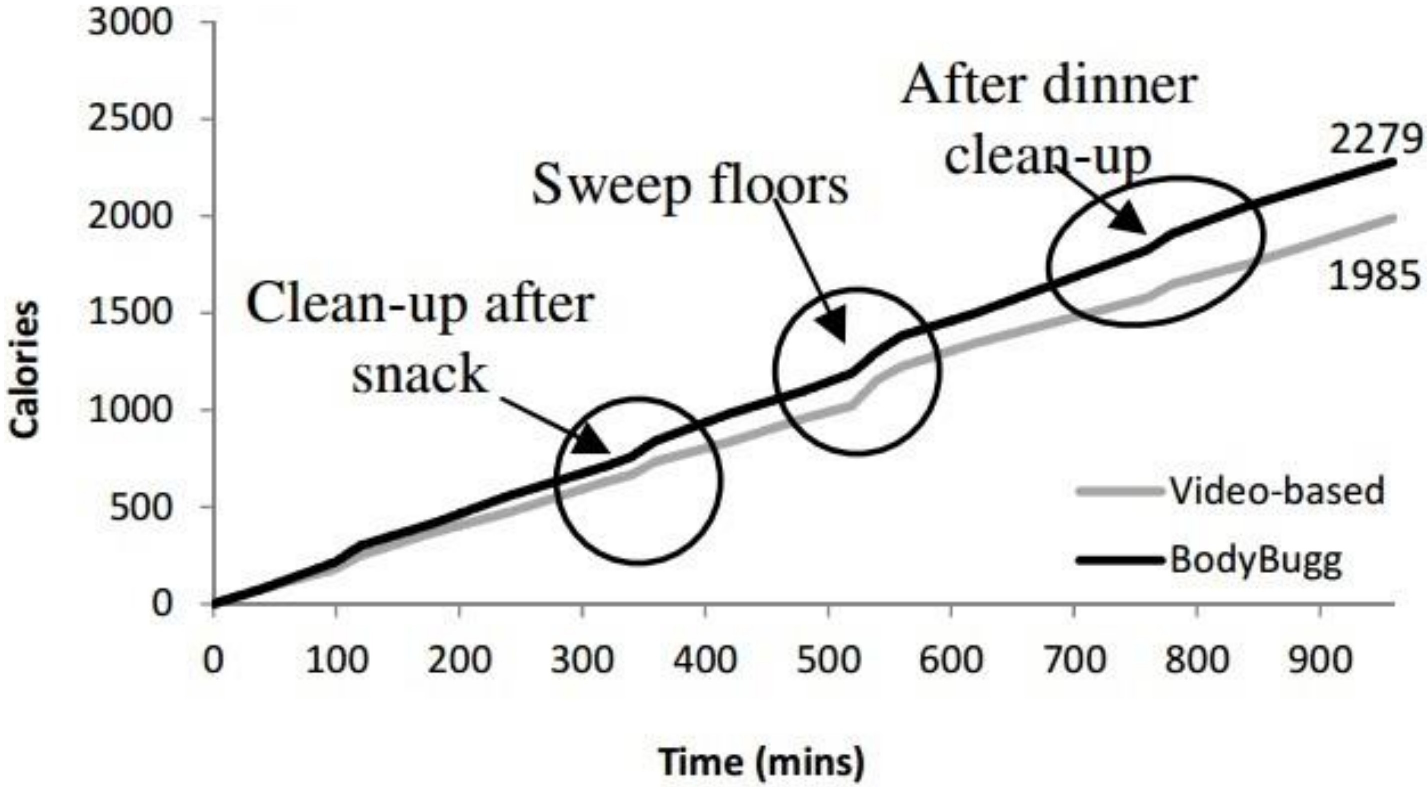
9 activities that each actor performed

Activity description	Energy expenditure level
Read while sitting	Low (< 3 Cal./min.)
Use laptop	Low
Eat while sitting	Low
Walk slowly	Medium
Clean surfaces	Medium
Sweep floors	High (> 6 Cal./min.)
Walk normally	High
Use stair stepper	High
Walk quickly	High

Energy expenditure estimation fidelity

Fidelity = correlation(video-based Calories, BodyBugg)

Actor 1's medium activity day



Daily energy estimation fidelity

Actor	Fidelity
1	r = 0.996
2	r = 1.000
3	r = 0.983
4	r = 0.997
Combined	**r = 0.997**

(Ideal is 1.0)

Daily energy estimation accuracy

Average accuracy over all actors = **90.9%**

Actor	Energy exp. level	BodyBugg estimate (Calories)	Video-based estimate (Calories)	Accuracy
1	Low	2128	1849	86.9%
1	Medium	2279	1985	87.1%
1	High	2407	2145	89.1%
…	…	…	…	…
3	Low	1993	1974	99.1%
3	Medium	2127	2042	96.0%
3	High	2331	2273	97.5%
…	…	…	…	…

Attempted refinements to improve fidelity and accuracy

- Added initial calibration phase (same results)

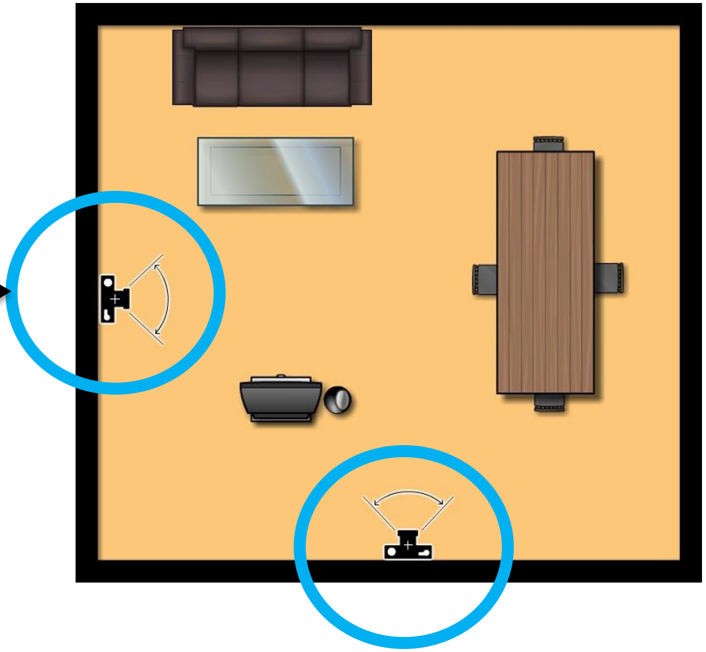


- Added orthogonal camera

  (same results)

- Use only orthogonal camera

  (decreased accuracy and fidelity)



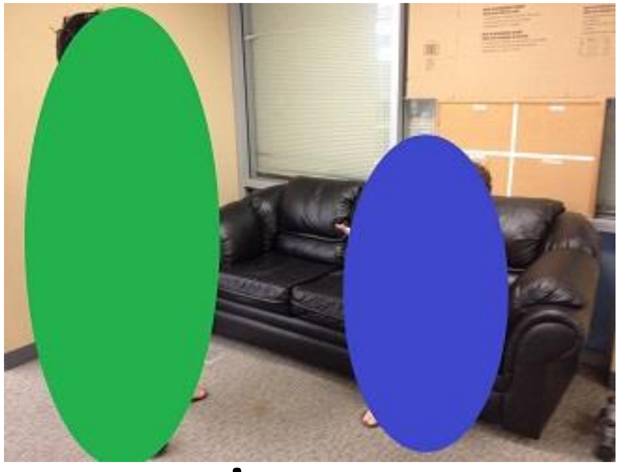
Limitations of cameras and this work

Not feasible locations

Not outside home

- BodyBugg ($150) had 90% accuracy vs. doubly labeled water ($30,000)
- Actors all male around age 20

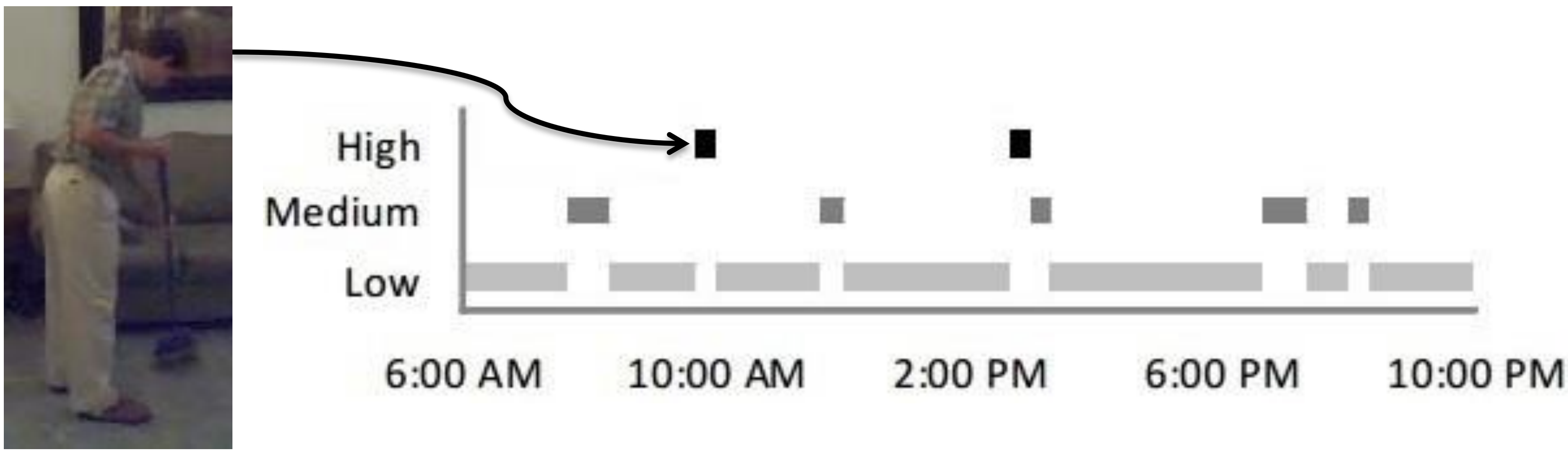
Future work



- Improve person tracker
  - Track only monitored person
  - Filter out pets, other motions
- Increase variability in experimentation
  - Resolution, direction, location, camera type, etc.
  - Include elder male and female actors
- Explore more elaborate feature selection
- Determine misleading activities

Conclusion

- Estimating energy from video is viable
- Simple and effective technique



- Video data set linked on my homepage:
  - http://www.cs.ucr.edu/~aedgcomb/

Complete reference list

[1] Courneya, et al. Relationships Among the Theory of Planning Behavior, Stages on Change, and Exercise Behavior in Older persons over a Three Year Period. Psychology and Health. Volume 13, Issue 2, 1998.

[2] Hirvensalo, et al. Mobility Difficulties and Physical Activity as Predictors of Mortality and loss of Independence in the Community-Living Older Population. Journal of the American Geriatrics Society. Volume 48, pgs. 493-498, 2000.

[3] Buchman, et al. Total Daily Physical Activity and the Risk of AD and cognitive Decline in Older Adults. Neurology. Volume 78, pgs.1323-1329, 2012.

[4] Lord, et al. The Effect of a 12-Month Exercise Trial on Balance, Strength, and Falls in Older Women: A Randomized Controlled Trial. Journal of Aging Physical Activity. Volume 43, pgs. 1198-1206, 1995.

[5] Fox, K.R. The Influence of Physical Activity on Mental Well-Being. Public Health Nutrition. Volume 2, pgs. 411-418, 1999.

[6] Zhang, et al. Improving Energy Expenditure Estimation for Physical Activity. Medicine and Science in Sports and Execise. Volume 36, pgs. 883-889, 2004.

[7] Yao, et al. A Video Processing Approach to the Study of Obesity. Multimedia and Expo. Pgs. 1727-1730, 2007.

[8] Choudhury, et al. The Mobile Sensing Platform: An Embedded Activity Recog. System. IEEE Pervasive Computing. Volume 7, pgs. 32-41, 2008.

[9] Tapia, et al. Activity Recognition in the Home Using Simple and Ubiquitous Sensors. Pervasive Computing: Lecture Notes in Computer Science. Volume 3001, pgs. 158-175, 2004.

[10] Zhou, et al. Activity Analysis, Sum., and Vis. for Indoor Human Activity Monitoring. IEEE Transactions on Circuits and Systems for Video Technology. Volume, 18, pgs. 1489-1498, 2008.

[11] Mayo Clinic. http://www.mayoclinic.com/health/exercise/SM00109. Sept. 2012.