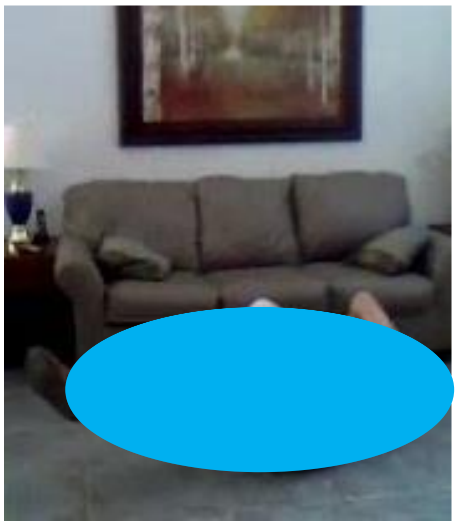
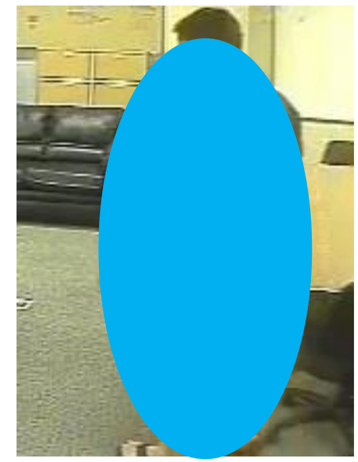
Automated In-Home Assistive Monitoring with Privacy-Enhanced Video





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Assistive monitoring goals

Fall detection

In region too long

Arisen in morning

Leave at night but not return

Unusually inactive

Energy trends

Reasons for video in assistive monitoring

Body-worn

Pro: Anywhere

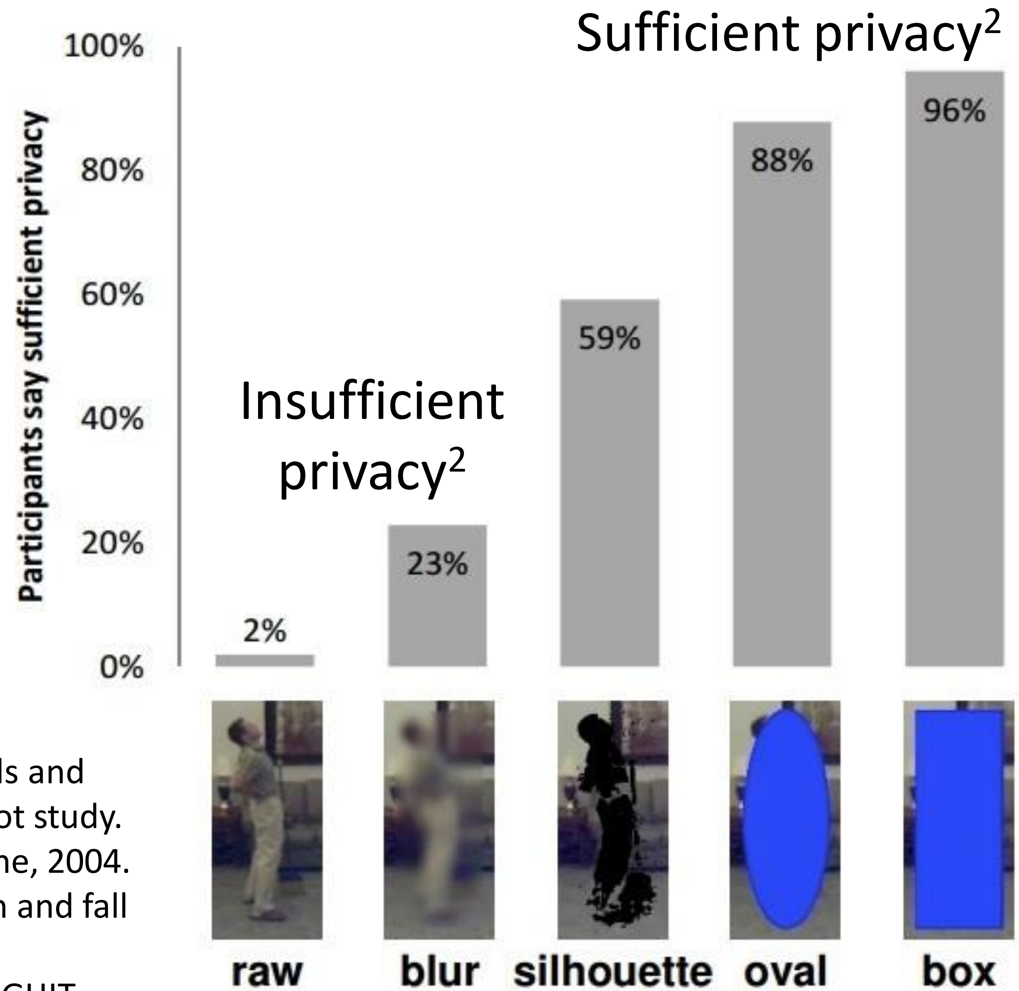
Con: Not always worn

Detect many events

Privacy enhance-able

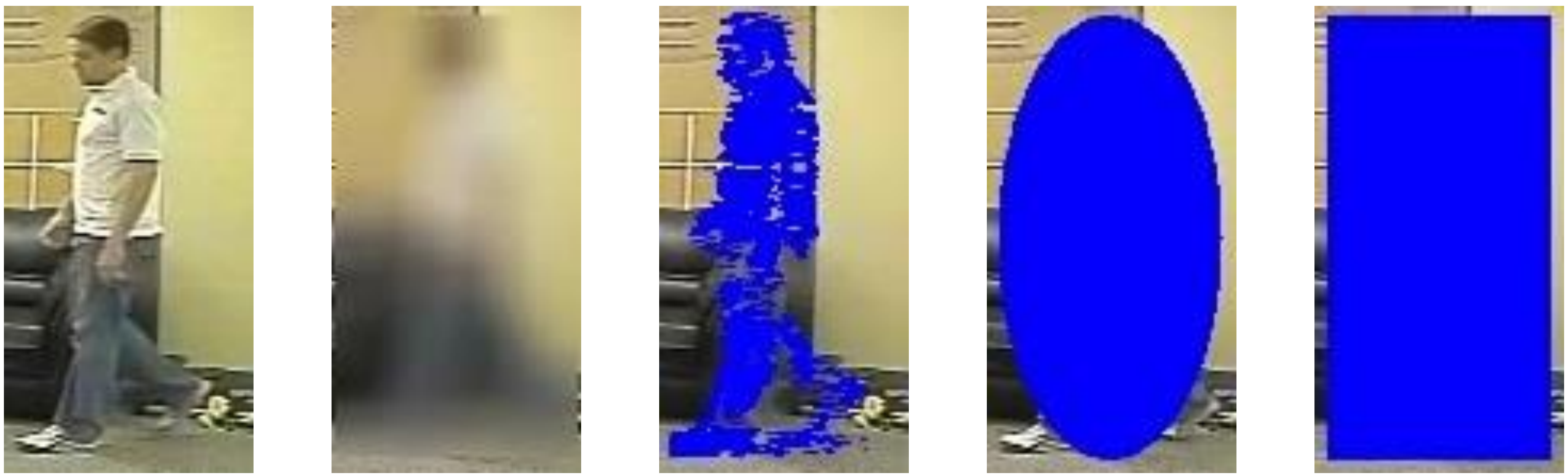
Reasons for privacy enhancements

- Participants age 65+ felt cameras were intrusive, while "many felt that [silhouetting] was more appropriate."[1]



[1] Demiris, et al. Older adults' attitudes towards and perceptions of 'smart home' technologies: a pilot study. Medical Informatics and The Internet in Medicine, 2004.
[2] Edgcomb, A. and F. Vahid. Privacy perception and fall detection accuracy for in-home video assistive monitoring with privacy enhancements, ACM SIGHIT (Special Interest Group on Health Informatics) Record, 2012.

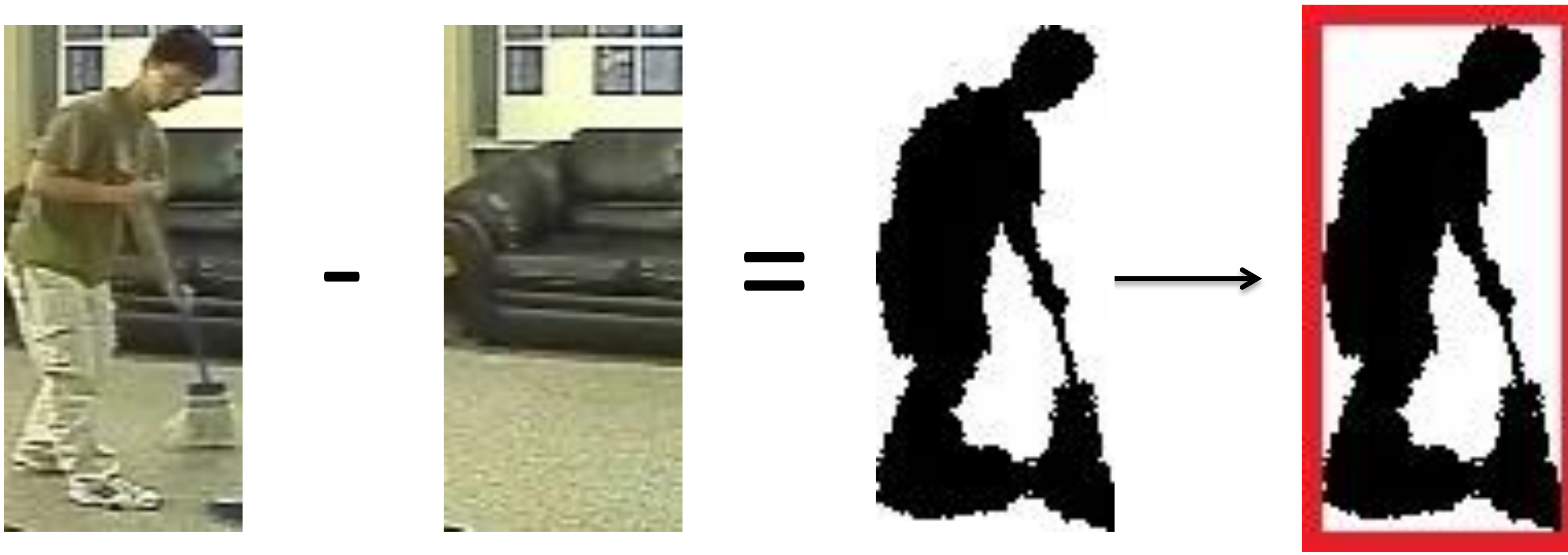
Privacy enhancements considered



Raw Blur Silhouette Oval Box

Person tracking and MBR extraction

via foreground-background segmentation



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

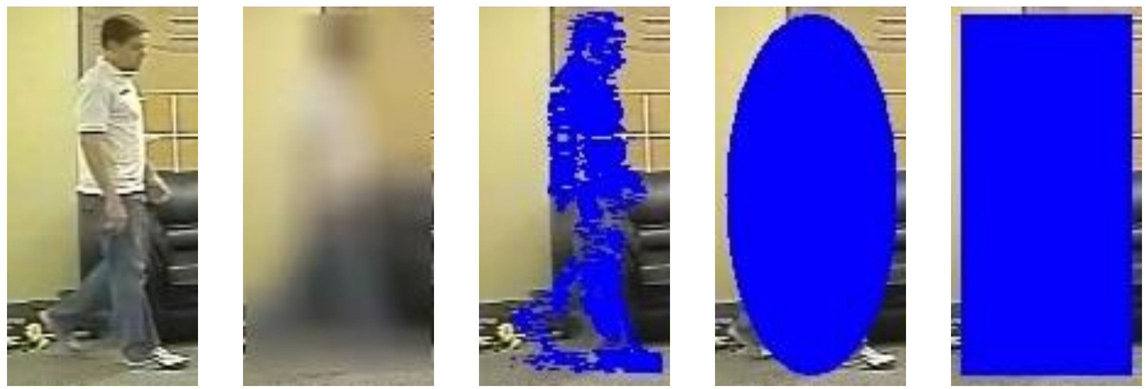
Recording environment

Energy expenditure estimation 1 of 2

BodyBugg

Fidelity = correlation(Video,BodyBugg)

0.997[3]   0.994   0.998   0.997   1.000



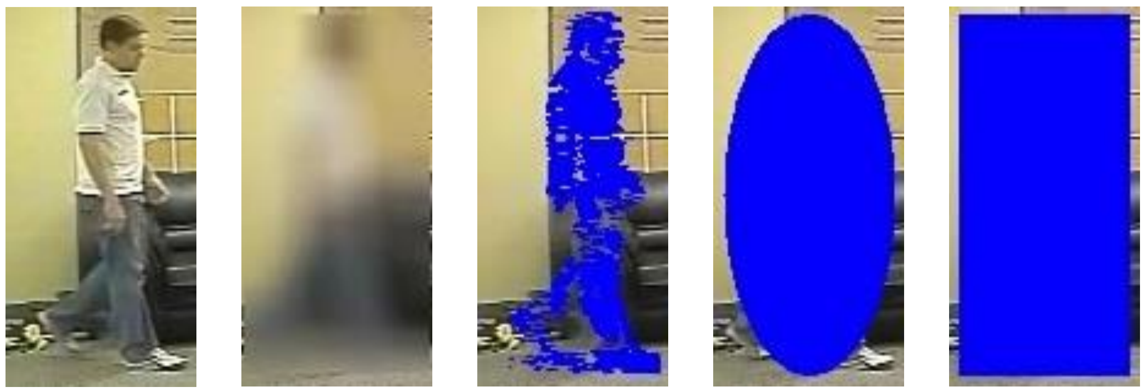
- Fidelity of privacy-enhanced video was the same as raw video ($p < 0.001$)

[3] Edgcomb, A. and F. Vahid. Estimating Daily Energy Expenditure from Video for Assistive Monitoring, IEEE International Conference on Healthcare Informatics (ICHI), 2013. (to appear)

Energy expenditure estimation 2 of 2

Accuracy

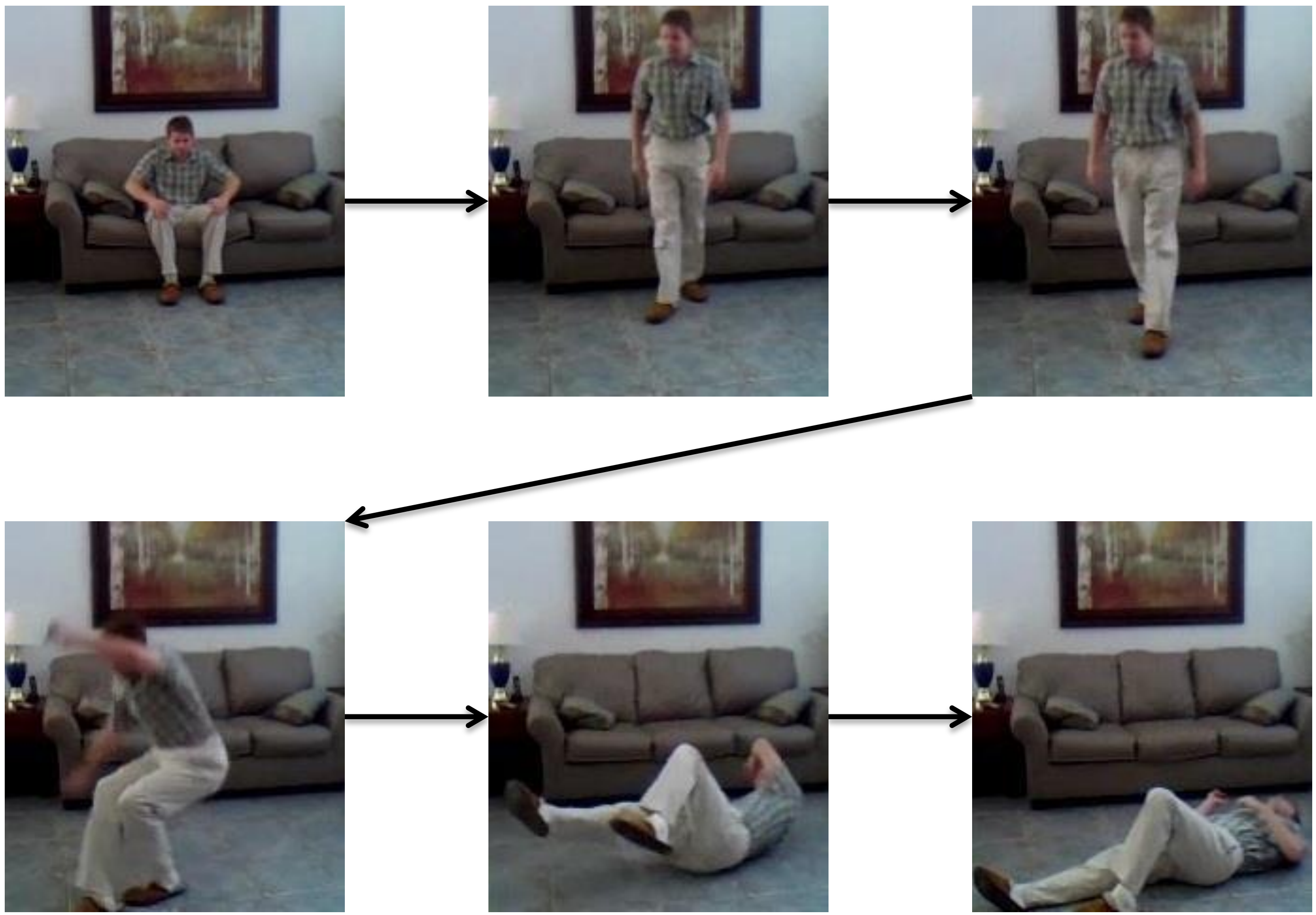
90.9%[3] 80.5% 85.0% 85.6% 84.3%



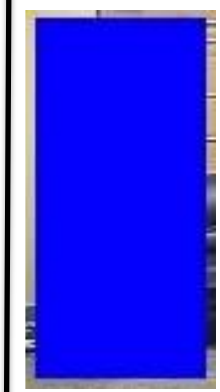
- Accuracy of privacy-enhanced video was less than raw video ($p < 0.001$)

[3] Edgcomb, A. and F. Vahid. Estimating Daily Energy Expenditure from Video for Assistive Monitoring, IEEE International Conference on Healthcare Informatics (ICHI), 2013. (to appear)

Fall detection 1 of 2



Fall detection 2 of 2

Sensitivity[4]	**0.91**	1.00	0.91	**0.91**	0.82
Specificity[4]	**0.92**	0.67	0.75	**0.92**	0.92
					

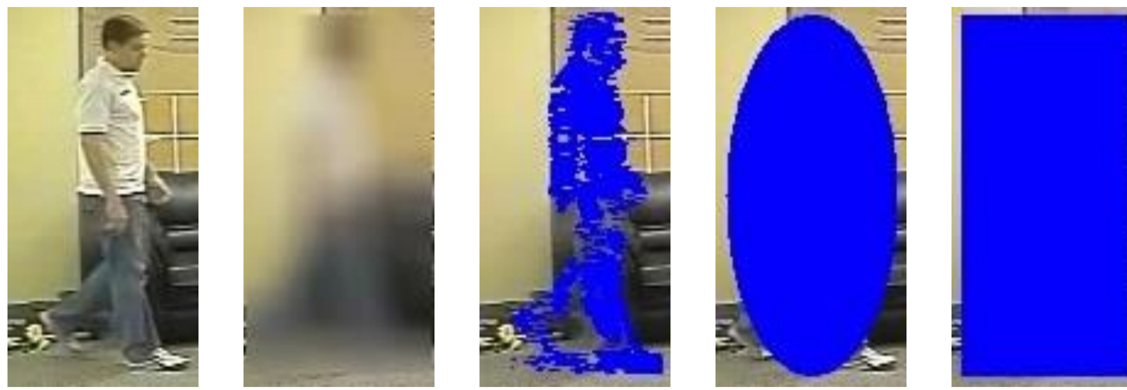
[4] Edgcomb, A. and F. Vahid. Automated Fall Detection on Privacy-Enhanced Video, IEEE Engineering in Medicine & Biology Society, 2012, 4 pages.

In-room-too-long, and leave-at-night-but-not-return

Exit from left
Enter to left

Sensitivity/Specificity

1.0/1.0 1.0/1.0 1.0/1.0 1.0/1.0 1.0/1.0



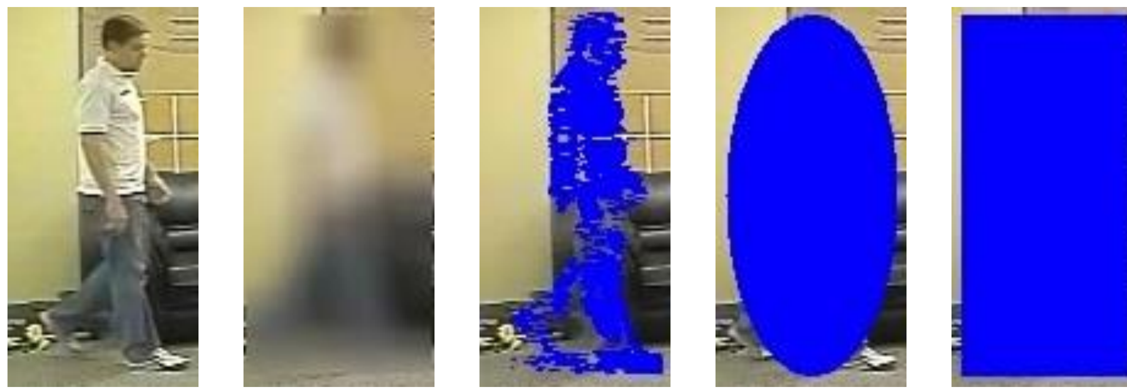
- Raw and privacy-enhanced video had perfect sensitivity and specificity

Arisen-in-morning, and not-arisen-in-morning

Arisen person enters main living area in morning

Sensitivity/Specificity

1.0/1.0 1.0/1.0 1.0/1.0 1.0/1.0 1.0/1.0



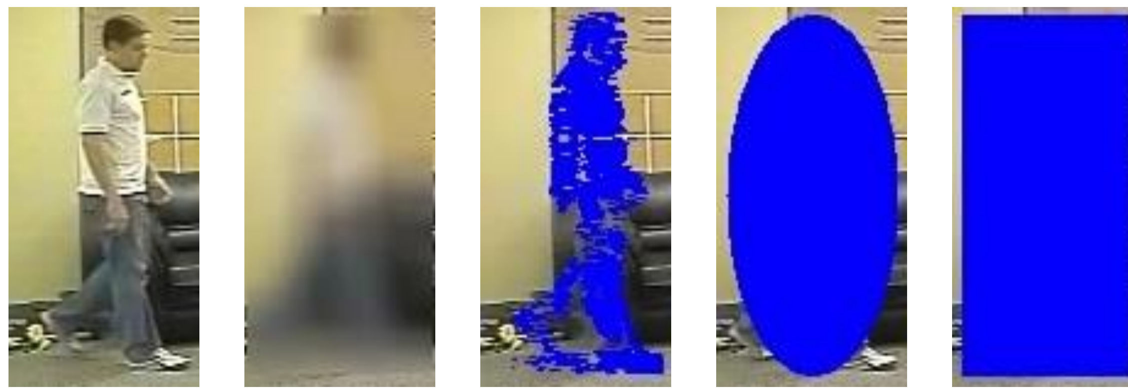
- Raw and privacy-enhanced video had perfect sensitivity and specificity

In region too long

Person in region

Sensitivity/Specificity

1.0/1.0 **0.5**/1.0 1.0/1.0 1.0/1.0 1.0/1.0



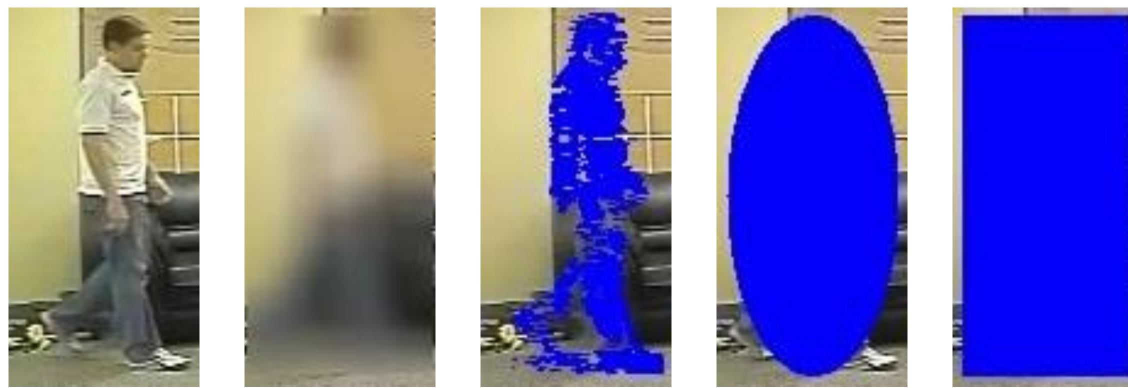
- Raw and privacy-enhanced video had perfect sensitivity and specificity, except blur's sensitivity.

Abnormally inactive during day

Person home but inactive for extended period

Sensitivity/Specificity

1.0/1.0 1.0/1.0 1.0/1.0 1.0/1.0 1.0/1.0



- Raw and privacy-enhanced video had perfect sensitivity and specificity

Most goals were achieved equally well even with privacy enhancements

	Energy estimation fidelity / accuracy	Fall detection sensitivity / specificity	In room too long sensitivity / specificity	Arisen in morning sensitivity / specificity	In region too long sensitivity / specificity	Abnormally inactive during day sensitivity / specificity
Raw	0.997 / 90.9%	0.91 / 0.92	1.0 / 1.0	1.0 / 1.0	1.0 / 1.0	1.0 / 1.0
Blur	0.994 / **80.5%**	1.00 / **0.67**	1.0 / 1.0	1.0 / 1.0	**0.5** / 1.0	1.0 / 1.0
Silhouette	0.998 / **85.0%**	0.91 / **0.75**	1.0 / 1.0	1.0 / 1.0	1.0 / 1.0	1.0 / 1.0
Oval	0.997 / **85.6%**	0.91 / 0.92	1.0 / 1.0	1.0 / 1.0	1.0 / 1.0	1.0 / 1.0
Box	1.000 / **84.3%**	**0.82 /** 0.92	1.0 / 1.0	1.0 / 1.0	1.0 / 1.0	1.0 / 1.0

Limitations of cameras and this work

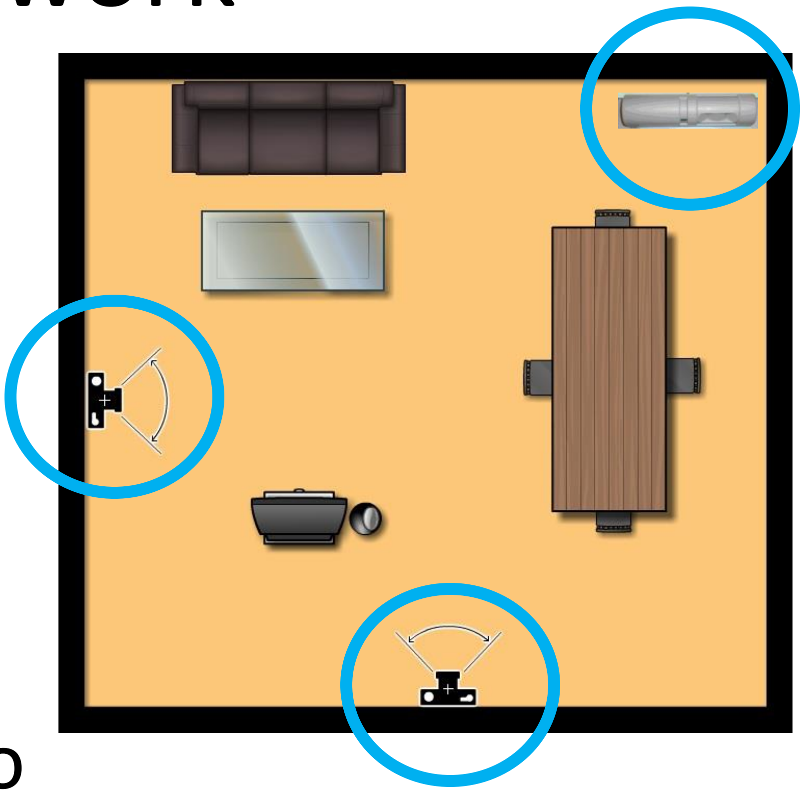
Not feasible locations

Not outside home

- Actors all males in 20s

Future work

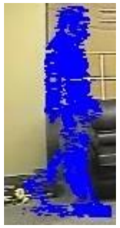
- Increase variability in experimentation
- Cameras and sensors working together



- Algorithms that adapt to the privacy enhancement[5]

[5] Edgcomb, A. and F. Vahid. Accurate and Efficient Algorithms that Adapt to Privacy-Enhanced Video for Improved Assistive Monitoring, ACM Transactions on Management Information Systems (TMIS): Special Issue on Informatics for Smart Health and Wellbeing, 2013. (to appear)

Conclusion

- Privacy-enhanced video is viable for 8 common monitoring goals
-  ,  , and  had little loss in goal achievement
- Blur had loss in goal achievement 
- Video data sets linked on my homepage:
  - http://www.cs.ucr.edu/~aedgcomb/