PlaceAvoider
Steering First-Person Cameras away from Sensitive Spaces
Robert Templeman, Mohammed Korayem, David Crandall, Apu Kapadia
Indiana University Bloomington
Cameras are commonplace in our computing landscape

http://www.steves-digicams.com/New-pope.jpg
Mobile cameras are not limited to smartphones

http://www.getnarrative.com
http://www.google.com/glass
http://www.vuzix.com
http://www.autographer.com
Wearable cameras have many interesting uses

Gordon Bell
logging his life since 2001

http://blog.autographer.com/2013/05/the-future-of-lifelogging-interview-with-gordon-bell/
Wearable cameras have many interesting uses.

- Saving precious moments
- Assisting with surgery
- Law enforcement
- Gordon Bell logging his life since 2001
- Therapeutic use
What about privacy?

Google Glass Is Banned On These Premises
http://www.bangkokpost.com
What about the device owner's privacy?
What about the device owner’s privacy?

Controlling the collection of images
CRePE - Conti et al.

Controlling access to images after collection
DARKLY - Jana et al.
What makes images sensitive?

what you are doing

where you are

who you are with

what objects are nearby
We seek to control images based on scene location

<table>
<thead>
<tr>
<th>Share</th>
<th>Don’t Share</th>
<th>Don’t Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>student lounge</td>
<td>conference room</td>
<td>bathroom</td>
</tr>
</tbody>
</table>

1. **Share**
   - Student lounge
   - Conference room
   - Bathroom

2. **Don’t Share**
   - Student lounge
   - Conference room
   - Bathroom
Existing localization has too much error

GPS accuracy ~ 5m
Network-based accuracy > 30m
Camera location may significantly differ from image scene location
PlaceAvoider concept

- 'student lounge' public access
- 'bathroom' forbidden

Policy

PlaceAvoider element
PlaceAvoider concept

- 'student lounge' + public access
- 'bathroom' + forbidden

Policy
Locale - Lindley Hall
'student lounge' - PUBLIC
'bathroom' - DELETE

PlaceAvoider element
PlaceAvoider concept

+ ‘student lounge’
  public access

+ ‘bathroom’
  forbidden

Policy
Locale - Lindley Hall
‘student lounge’ - PUBLIC
‘bathroom’ - DELETE

Classifier

Policy Enforcement

PlaceAvoider element
PlaceAvoider within the OS

Policy
Locale - Lindley Hall
'student lounge' - PUBLIC
'bathroom' - DELETE

Classifier

Policy Enforcement

X X
PlaceAvoider in the cloud

Cloud service

Policy
Locale - Lindley Hall
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Classifier

Policy Enforcement

public life log

PlaceAvoider element
PlaceAvoider in the cloud

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Policy Enforcement

Classifier

public life log

PlaceAvoider element

lifelogging appliance
PlaceAvoider classifier

local image feature classifier

HMM

global image feature classifier

space= __________

space= bathroom

space= __________

space= bathroom

space= __________

space= student lounge
Two types of image features

Local image features describe a sub-region of a spatial image
- key point detector SIFT

Global image features describe an entire image
- sparse SIFT
- dense grid SIFT
- grid HOG

http://www.vlfeat.org/overview/sift.html
Matching with **distinctive** features

bathroom

lab
Matching with *distinctive* features

SIFT feature detector identifies *interesting* features
Matching with distinctive features

bathroom

lab

similar features across spaces offer no discriminative value
Matching with *distinctive* features

bathroom  lab

represent scenes via discriminating features
Matching with *distinctive* features

\[ \frac{|f? - f_{bathroom}|}{|f? - f_{office}|} > \tau \]

This feature is not distinctive
Matching with \textit{distinctive} features

\[ \frac{|f? - f_{bathroom}|}{|f? - f_{office}|} \leq \tau \]

\( f_{bathroom} \)  
\( f_{office} \)

this feature IS distinctive
Color histograms

Original image

Red, green, and blue color channels

Histograms over pixel intensities
Modeling scene textures (HOG)
Modeling scene textures (HOG)

original image

partitioned in 8x8 windows
Modeling scene textures (HOG)

- Original image
- Partitioned in 8x8 windows
- Compute distribution of edge orientations in each window
Modeling scene textures (HOG)

original image

partitioned in 8x8 windows

compute distribution of edge orientations in each window

histogram over edge orientation patterns
Classifying photo streams with HMMs

Probabilities with individual photo classifiers:

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<tr>
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Classifying photo streams with HMMs

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- Green checkmark indicates a correct classification.
- Red X indicates an incorrect classification.
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<tr>
<td><img src="image1" alt="Bathroom Image" /></td>
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<td><img src="image4" alt="Living Image" /></td>
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**Probabilities with individual photo classifiers:**

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**Probabilities after applying HMM:**

| Bathroom: 0.896 | 0.436 | 0.060 | 0.015 | 0.010 | 0.006 | 0.002 | 0.000 |
| Bedroom: 0.010 | 0.052 | 0.026 | 0.004 | 0.002 | 0.002 | 0.002 | 0.000 |
| Garage: 0.009 | 0.045 | 0.024 | 0.004 | 0.002 | 0.002 | 0.006 | 0.001 |
| Living: 0.079 | 0.441 | 0.881 | 0.968 | 0.975 | 0.873 | 0.125 | 0.005 |
| Office: 0.006 | 0.027 | 0.009 | 0.009 | 0.012 | 0.116 | 0.865 | 0.994 |
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Evaluation
We evaluated PlaceAvoider in 5 settings

2 office buildings and 3 homes (authors’) 
5 rooms evaluated at each location

**Enrollment imagesets**
deliberately captured 
not structured (cover a space) 
average of 70 images per space

**Test imagesets**
opportunistically captured, ~3s frequency 
temporally ordered (stream) 
323 to 629 images per location
Local features perform better at classifying single images

<table>
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<tr>
<th>Dataset</th>
<th>Baseline</th>
<th>Local features</th>
<th>Global features</th>
</tr>
</thead>
<tbody>
<tr>
<td>House 1</td>
<td>29.8%</td>
<td>52.9%</td>
<td>48.3%</td>
</tr>
<tr>
<td>House 2</td>
<td>31.0%</td>
<td>41.8%</td>
<td>49.1%</td>
</tr>
<tr>
<td>House 3</td>
<td>20.9%</td>
<td>81.5%</td>
<td>80.0%</td>
</tr>
<tr>
<td>Workplace 1</td>
<td>32.1%</td>
<td>75.9%</td>
<td>74.6%</td>
</tr>
<tr>
<td>Workplace 2</td>
<td>28.9%</td>
<td>71.6%</td>
<td>69.4%</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>28.5%</td>
<td><strong>64.7%</strong></td>
<td><strong>64.3%</strong></td>
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</table>
Joint classifier with HMM provides much higher accuracy

<table>
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<tr>
<th>Dataset</th>
<th>Baseline</th>
<th>Local features + HMM</th>
<th>Global features + HMM</th>
<th>Local+global features + HMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>House 1</td>
<td>29.8%</td>
<td>89.2%</td>
<td>64.0%</td>
<td>89.2%</td>
</tr>
<tr>
<td>House 2</td>
<td>31.0%</td>
<td>55.0%</td>
<td>56.4%</td>
<td>74.6%</td>
</tr>
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<td>House 3</td>
<td>20.9%</td>
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<td>98.7%</td>
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PlaceAvoider is robust in the presence of scene occlusion

apply 30% mask to a random fraction of images in the workplace 2 stream

<table>
<thead>
<tr>
<th>% of occluded images in stream</th>
<th>Local classifier accuracy</th>
<th>Global classifier accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>71.6%</td>
<td>69.4%</td>
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<tr>
<td>100</td>
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PlaceAvoider is robust in the presence of scene occlusion.

apply 30% mask to a random fraction of images in the workplace 2 stream.

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Running time for prototype system

Feature extraction and classification: 18.421 seconds.

Classifier framework: R
SIFT feature extraction: Lowe’s binary
Classifier components: C++, Python, R

Hardware: 2.6 GHz Xeon workstation (one thread)
Feature extraction and classification: 18.421 seconds.

Classifier framework: R
SIFT feature extraction: Lowe's binary
Classifier components: C++, Python, R

Hardware: 2.6 GHz Xeon workstation

Running time for prototype system

- Baseline classifier
- Lightweight classifier

Accuracy (%)

- local SIFT
- global sparse SIFT
- global dense SIFT
- global HOG
Discussion

System improvements
- more usable enrollment
- topological mapping

Other sensitive content types
- policies that control imaging of sensitive objects

Protecting the privacy of bystanders
- making others enforce your policies
In conclusion...

Modern camera devices make it too easy to collect and share images.

PlaceAvoider explores imposing boundaries on where cameras can be used.

Much work remains to be done to explore other attempts to classify sensitive images.
Questions?

Mohammed Korayem

David Crandall

Apu Kapadia
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