I MADE A SIGN

MY SIGN IS BETTER THAN HIS
Can you find them in this photo?
Where’s Waldo?
Manually matched photos from a collection of 282
Automatically matched photos from a collection of 282
**Problems:** Severe occlusion, Varying poses and cameras, Low resolution

- Non-rigid Pose Change
- Severe Occlusion
- Low Resolution
- Photos from hundreds of users, Different viewpoints
**Problems:** Severe occlusion, Varying poses and cameras, Low resolution

- **Scene Geometry And Camera Pose**
- **Part based appearance model** based on cloth color
- **Detection and Recognition**
  - **Time stamps:** people are relatively still over short intervals
  - **Co-occurrence cues:** People move about with same set of people
Details of the approach
Learn Appearance Classifier → 3D Localization → MRF Refinement

Single labeled instance
Learn Appearance Classifier

3D Localization

MRF Refinement

Single labeled instance
Appearance Classifier

**User Input:** $\rho_{\text{head}}, \rho_{\text{ground}}$, masks for head, torso and legs on a single query image.

**Learn:** pixel level RGB classifier using logistic regression for the three parts.

**Scoring a candidate:** Align the candidate with the template. Run the part classifiers and sum the pixel classification weighted using part masks.
Key Idea
Generalization of Multi View Stereo (MVS)

Assumptions: Known camera pose, small person movement over short time interval
3D Localization

Propose candidate locations by back-projecting rays from query image. Project candidate locations into other images and score these images using learnt classifier.

**Height Prior:** Prior on average height of a person.

**Ground Prior:** Encourage back-projection of \( p_{ground} \) to be close to the ground plane in 3D.
Learn Appearance Classifier → 3D Localization → MRF Refinement
Markov Random Field Refinement

Choose 3D location with highest score for each person. Project into each image and decide which projections are true matches. Use **co-occurrence** and **time** cues.

**Co-occurrence and Time Cues:**
- People appear with the same group of people.
- Images nearby in time are likely to contain the same people.
Node for every person-image pair, \((p_i, l_j)\).
Solve for a binary labelling where label = 1 if \(p_i\) occurs in \(l_j\).

Add edges linking people who appear together and between images that are close in time.

Use graph cuts to select the best candidate matches for each person.
The Markov Random Field Model

likely to appear together
likely to contain same people

Images
Results
Ground Truth

All datasets downloaded from Flickr and manually matched.
Results: Dataset 1

34 photos taken by a single photographer at Trafalgar Square on a single day. 16 different people to match, 130 total matches.

Sample matching result for one person: 7/9 matches found. The query image was a back pose while the found matches are all side poses. There are two missed matches, one with extreme pose change and the other with severe occlusion.
precision
Results: Dataset 2

282 photos taken by 89 different photographers at Trafalgar Square on a single day. 57 people, 244 total matches.

A representative result: 6/7 matches found are correct. One of the missed matches has extreme occlusion and the false positive is due to presence of a similar color.
Results: Dataset 3

45 photos from 19 different users taken during an indoor event – Hackday London 2007 over two days. 16 people, 56 matches.

All 5 matches are found. Note that the laptop is not visible in the query image.
Conclusions

• Very hard problem made tractable by simplifying assumptions: Known camera pose, relatively static people

• Relax assumptions in future: “track” people from photos, use stronger appearance cues in photos with unknown camera pose

• Lack of datasets presently – will change with more cameras and more photo sharing
Discussion
Relaxing restrictions

How might we relax some of the restrictions in order to work with more diverse image sets?

1. How to handle moving people?
2. Horizontal (sleeping) people?
3. People on stairs, stages, pyramids?
4. Dramatic changes in pose?
5. Changes in clothing?
6. Lighting changes?
Relaxing restrictions

How might we relax some of the restrictions in order to work with more diverse image sets?

- Could you use A* or other iterative search techniques to broaden searches adaptively?
- Identify a separate set of matches after big changes?
Improvements

Are there other features or strategies that might improve the model?
Improvements

Are there other features or strategies that might improve the model?

• Augmenting the appearance model with facial recognition
• Texture recognition
User interactions

What interactions might you build on top of this?
User interactions

What interactions might you build on top of this?

• **How to navigate a photo set based on correspondences?**
  – Could you interactively pivot between photos by selecting individual people?
  – Center or highlight people of interest in a PhotoSynth-style environment and focus on the images that contain them?
  – Display many images of a target individual as small multiples?

• **Could you use user feedback to improve results?**
User interactions

Could you use user feedback to improve results?
User interactions

Could you use user feedback to improve results?

• *Contextual cues encourage people with high affinities to share detections among them. A side effect is that false positives and false negatives are also shared. More user interaction may be helpful here, i.e., correcting a match for a single person may correct it for a number of other people as well.*
Other domains

How might you alter this approach to work for other applications?
Other domains

How might you alter this approach to work for other applications?

• Cars?
• Wildlife tracking?
• etc.?
Applications

What applications does the paper suggest?
Do these seem useful?
Can you think of other applications?
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Do these seem useful?
Can you think of other applications?

• *Photo tagging*
• *Navigating photo archives*
• *Surveillance*
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The Markov Random Field Model

Node for every person-image pair, \((p_i,l_j)\).
Solve for a binary labelling where label = 1 if \(p_i\) occurs in \(l_j\).

Add edges between people with weights determined by \textit{people affinity}, edges between images with weights determined by \textit{image affinity}.

**Image Affinity:**
\[
\alpha_I(I_j, I_{j'}) = \lambda_1 e^{-|t_{j} - t_{j'}|^2 / 2\sigma^2_t}
\]
where \(t_i\) is the corresponding time stamp.

**People Affinity:**
\[
\alpha_p(p_i, p_{i'}) = \lambda_2 \frac{|D_i \cap D_{i'}|}{|D_i| + |D_{i'}|}
\]
where \(D_i\) is the set of images that contain \(p_i\).
Solve MRF iteratively updating \(D_i\) each time.