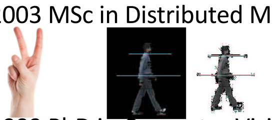
Egocentric Vision

Dr Dima Damen
Department of Computer Science

Short Bio

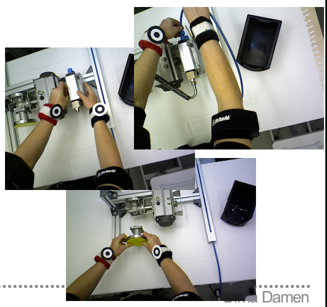
- 1998-2002 BSC in Computer Science
- 2002-2003 MSc in Distributed Multimedia Sys.



- 2006-2009 PhD in Computer Vision

Short Bio

- 2010-2012 Postdoc on EU-FP7 project



Short Bio

- 2013-2017 Assistant Prof in Computer Vision
- 2017- Associate Prof in Computer Vision

Egocentric Vision?

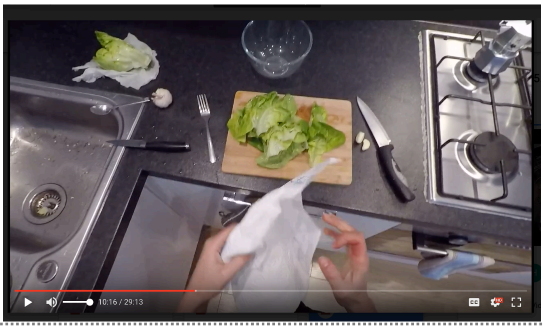
- Research interests: action and activity recognition
- Particularly centred around the perception of object interactions

Ego…

Ego… a person's sense of self-esteem or self-importance

Egocentric vision… the wearer serves as the central reference point in the study of interesting entities: objects, actions, interactions and intentions

Ego…



Visual Sensing – the landscape

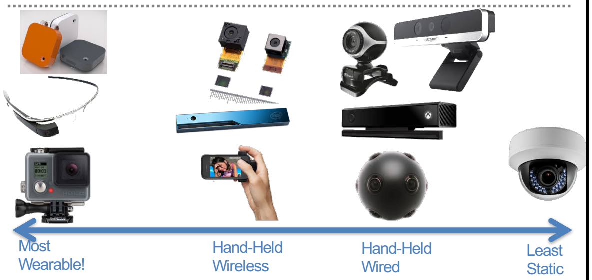
Visual Sensing – the landscape

Expensive

Visual Sensing – the landscape

Moveable

Visual Sensing – the landscape



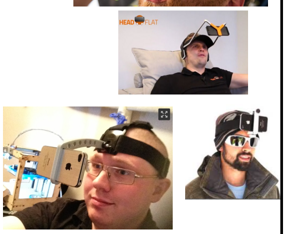
Wearable

Wearable?

Wearable?

Wearable?

Wearable?

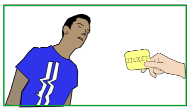
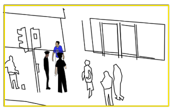


Wearable?

- Hat-Mounted
- Head-Mounted
- Glass-Mounted
- Shoulder-Mounted
- Chest-Mounted
- Wrist-Mounted
- Belt-Mounted
- Ankle-Mounted

But why do we care about… hardware???

- OPV (Ordinal-Person Views)
  - FPV (First-Person View)
  - SPV (Second-Person View)
  - TPV (Third-Person View)

See for yourself!

- Videos…

Top-Left: Fathi – Disney dataset for social interactions 2012
Top-Right Damen EPIC-Kitchen 2017
Bottom-Left Damen BEOID 2014
Bottom-Right Kitani (Youtube) Sports 2011

Conclusions?

- Just another camera?
- Just a shaking camera?

Egocentric Vision

- The Unique Problems
  1. Camera Motion
  2. Mapping and Localisation
  3. Attention and Task-Relevance
  4. Object Interactions
  5. Multi-view Solutions
- The Unique Applications
  1. Video Summarisation
  2. Skill Determination
  3. Real-time solutions

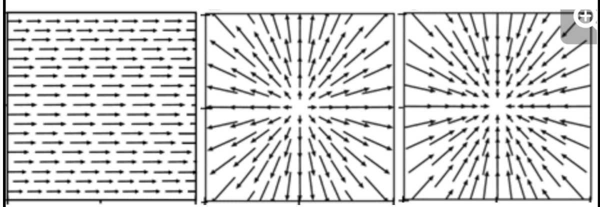
The Unique Problems

1. Camera Motion

1. Camera Motion

- Two types of motion
  - Egomotion
  - Foreground motion

Ego-motion



rotating approaching receding

Ego-motion

- Detect to:
  - Use?
  - Remove?

Hyperlapse

- https://youtu.be/sA4Za3Hv6ng

The Unique Problems

2. Mapping and Localisation

Mapping and Localisation

- https://youtu.be/ufBLu1VUQ-E

The Unique Problems

3. Attention and Task Relevance

Attention and Task Relevance

- What is attention?
  - Non-Egocentric Attention Models (→ Saliency)

DUT-OMRON dataset
http://saliencydetection.net/dut-omron

Attention and Task Relevance

- What is attention?
  - Non-Egocentric Attention Models (→ Saliency)

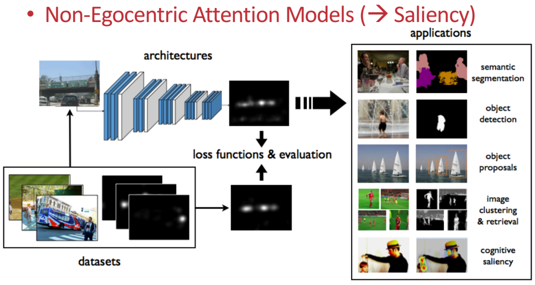
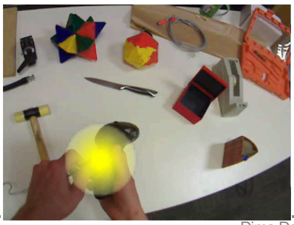


Figure: Zoya Bylinskii & Tilke Judd, ECCV 2016 Tutorial
http://saliency.mit.edu/ECCVTutorial/newDirectionsInSaliency.pdf

Attention and Task Relevance

Attention and Task Relevance

- Attention in egocentric vision
  - Foreground segmentation
  - Hand-region segmentation
  - Gaze tracking



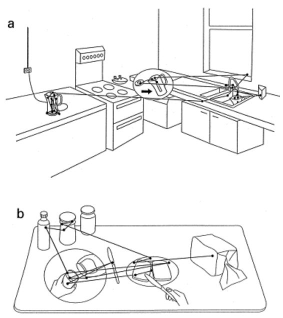
Quick introduction to human gaze

- Humans iterate between "fixations" and "saccades"
  - Fixation: short stops
  - Saccade: quick movements between fixations
- https://youtu.be/pknohrsz4Qs

Quick introduction to human gaze

Quick introduction to human gaze

Quick introduction to human gaze



Land and Hayhoe (2001) In what ways do eye movements contribute to everyday activities? Vision Research

Quick introduction to human gaze

- The notion of fixation/saccade has recently inspired attention models in vision

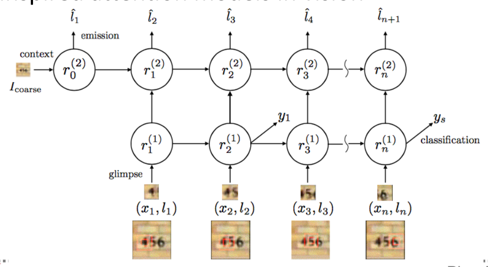


Figure: Lei Ba et al (2015). Multiple Object Recognition with Visual Attention. ICLR

The Unique Problems

3. Attention and Task Relevance

Case Study: You-Do, I-Learn

You-Do, I-Learn

with: Walterio Mayol-Cuevas
Teesid Leelasawassuk

- First-person view
- Offers a unique insight into 'used' or 'attended-to' objects
- How these objects have been used

D Damen, T Leelasawassuk, W Mayol-Cuevas (2016). You-Do, I-Learn: Egocentric Unsupervised Discovery of Objects and their Modes of Interaction Towards Video-Based Guidance. *Computer Vision and Image Understanding*

Try it yourself

with: Walterio Mayol-Cuevas
Teesid Leelasawassuk

You-Do, I-Learn

- Q. How to 'ground-truth' objects that have been used?
- Q. How to 'ground-truth' how these objects have been used?

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with: Walterio Mayol-Cuevas
Teesid Leelasawassuk

BEOID

- Ground-truth by written narration
- Released with dataset

pick the charger and plug it into the socket. Check that the screwdriver is powered by looking at the button. Pick the tape and place it in the box. Walk to the printer. Open the drawer to check the paper, and press keys on the printer pad. Use the card to unlock the door

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Action

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Teesid Leelasawassuk

You Do, I Learn

- Discover used objects
- Discover how objects have been used
- Extract guidance videos
- Fully unsupervised
  - No prior knowledge of objects (number, size)
  - Static and moveable objects

Action

with: Walterio Mayol-Cuevas
Teesid Leelasawassuk

Definition

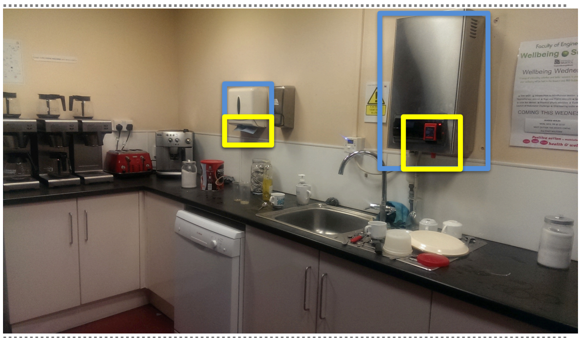
Task-Relevant Object (TRO)

an object, or part of an object, with which a person interacts during task performance

Action

with: Walterio Mayol-Cuevas
Teesid Leelasawassuk

Which Objects?



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Teesid Leelasawassuk

Discovering Task-Relevant Objects

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Teesid Leelasawassuk

Discovering Task-Relevant Objects

- *Suggested* Problem Formulation…
  - Given a sequence of egocentric images $\{I_1, .., I_T\}$
  - Collected from multiple operators around a common environment
  - Automatically discover all task-relevant objects

$$\{O_k; 1 \leq k \leq K\}$$

$$O_k = \{\Omega(I_t); 1 \leq t \leq T\}$$

  - *Assumption:* at most one task-relevant image part is present within each image

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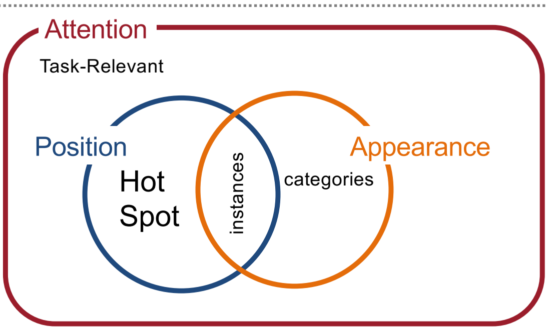
Teesid Leelasawassuk

Discovering Task-Relevant Objects



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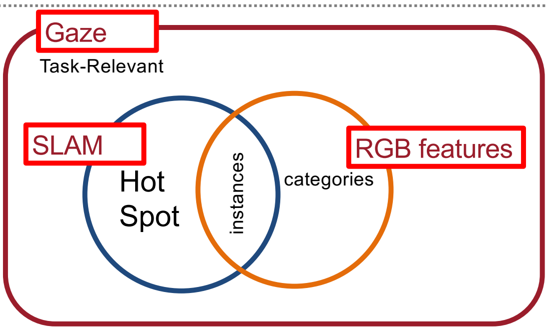
Discovering Task-Relevant Objects



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Discovering TROs

Discovering becomes a clustering task…

- Considers attention, position and appearance
- Unknown number of objects

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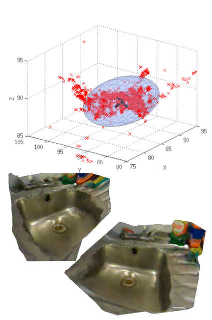
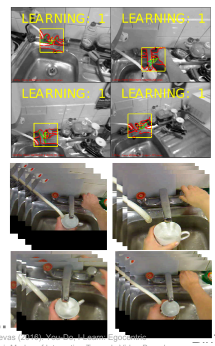
Discovering Task-Relevant Objects





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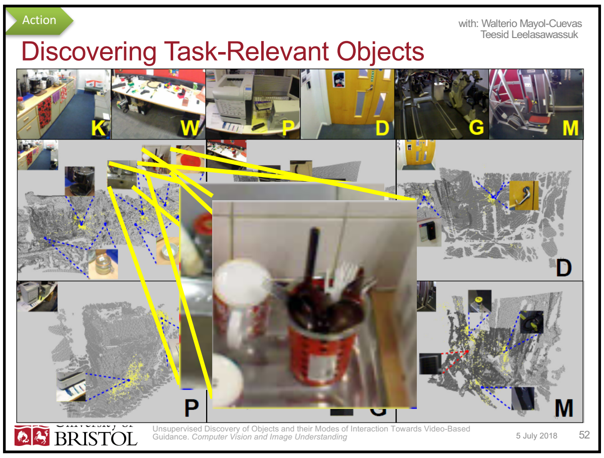
Action
with: Walterio Mayol-Cuevas
Teesid Leelasawassuk
Discovering Task-Relevant Objects
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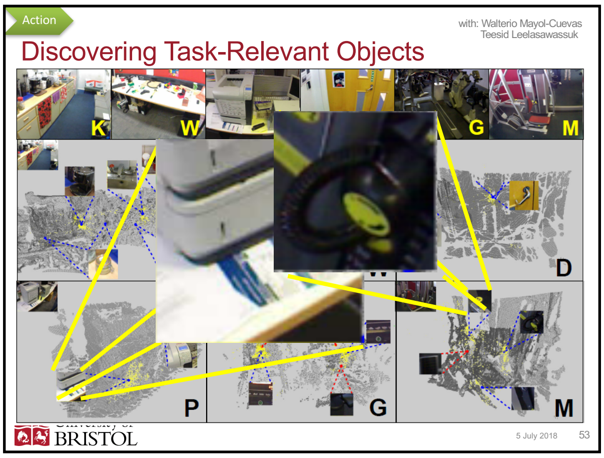
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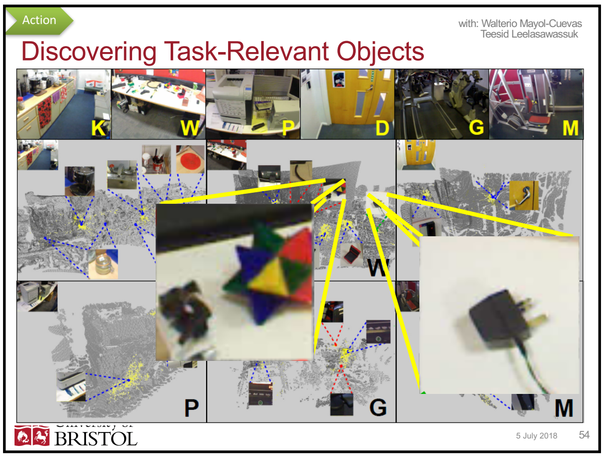
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Action

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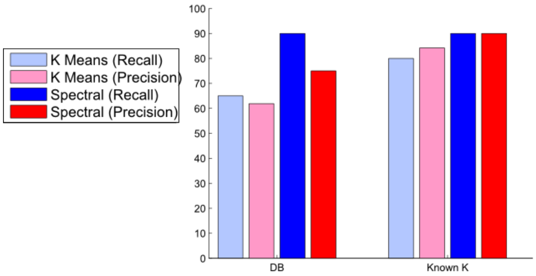
Discovering Task-Relevant Objects



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Action

with: Walterio Mayol-Cuevas
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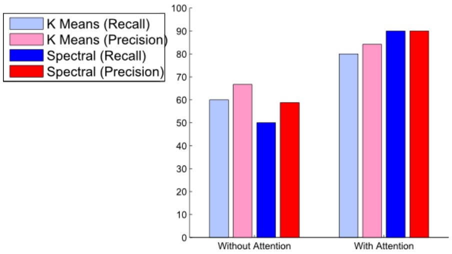
Discovering Task-Relevant Objects



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Discovering Modes of Interaction

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Definition

Modes of Interaction (MOI)

the different ways in which TROs are used

Action

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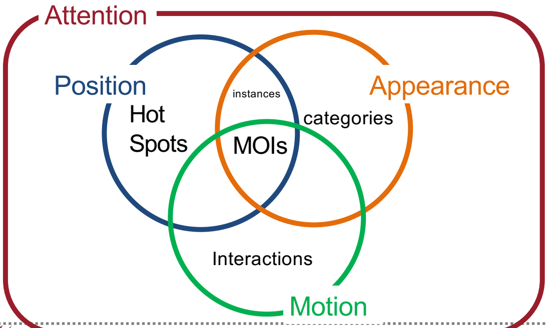
Discovering Modes of Interaction



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Discovering Modes of Interaction

- Motion
  - Video snippets for each discovered object
  - Descriptor per snippet
  - Clustering using DB-index

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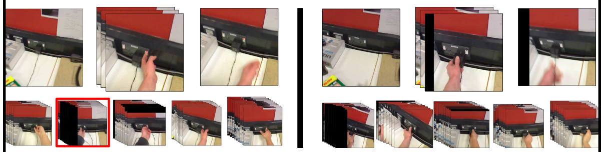
Discovering Modes of Interaction



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Action

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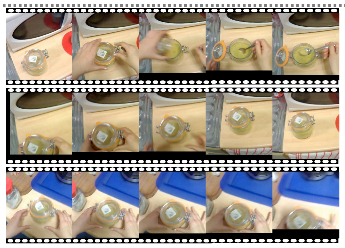
Discovering Modes of Interaction

Open & get sugar

Put

Pick



Open door

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Action

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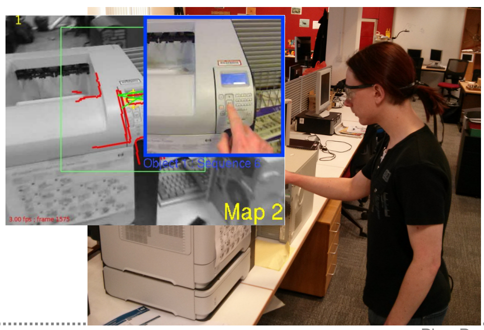
Back to…. the goal…



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You Do, I Learn - Demonstration

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More info…

Project You-Do, I-Learn

Video1 (2014), Video2 (2017)

Automated capture and delivery of assistive task guidance with an eyewear computer: The GlaciAR system. T Leelasawassuk, D Damen, W Mayol-Cuevas. Augmented Human, Mar 2017 pdf

You-Do, I-Learn: Discovering Task Relevant Objects and their Modes of Interaction from Multi-User Egocentric Video. D Damen, T Leelasawassuk, O Haines, A Calway, W Mayol-Cuevas. British Machine Vision Conference (BMVC), Sep 2014. PDF | Abstract | Dataset

Multi-user egocentric Online System for Unsupervised Assistance on Object Usage. D Damen, O Haines, T Leelasawassuk, A Calway, W Mayol-Cuevas. ECCV Workshop on Assistive Computer Vision and Robotics (ACVR), Sep 2014. PDF Preprint

Estimating Visual Attention from a Head Mounted IMU. T Leelasawassuk, D Damen, W Mayol-Cuevas. International Symposium on Wearable Computers (ISWC), Sep 2015. PDF

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The Unique Problems

4. Object Interactions

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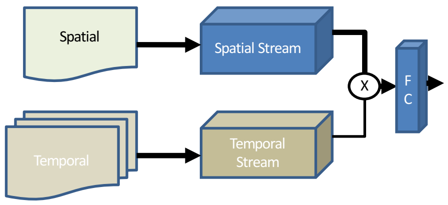
Action Recognition – an Introduction

- CNNs for Action Recognition
  1. Dual-Stream Neural Networks



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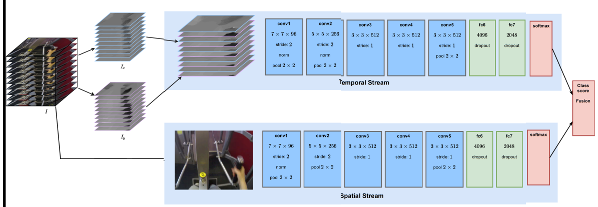


Figure by: Will Price, BSc Project, University of Bristol

Egocentric Action Recognition

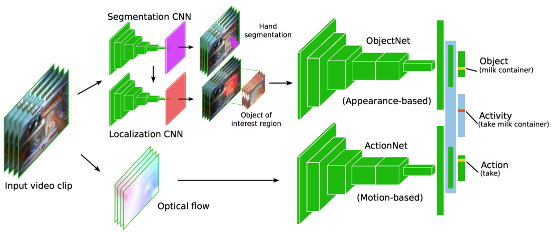
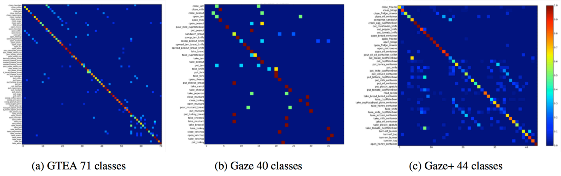
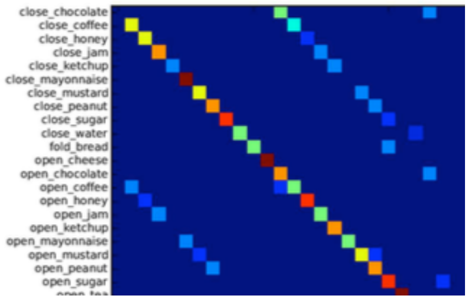


Figure from: Ma et al. Going Deeper into First-Person Activity Recognition. CVPR 2016

Egocentric Action Recognition



Egocentric Action Recognition



Action Recognition – an Introduction

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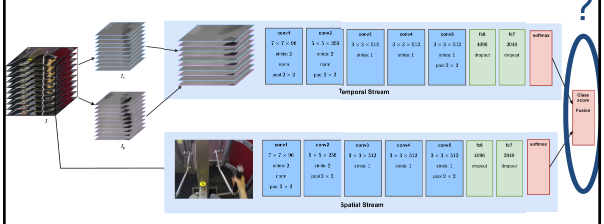
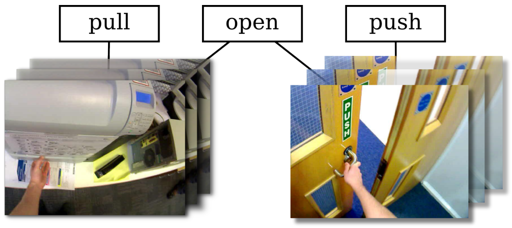


with: Michael Wray
Davide Moltisanti
Walterio Mayol-Cuevas

Object Interactions – the Dilemma



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M Wray et al (2018). Towards an Unequivocal Representation of Actions. Arxiv.
M Wray et al (2017). Improving Classification by Improving Labelling: Introducing Probabilistic Multi-Label Object Interaction Recognition. Arxiv

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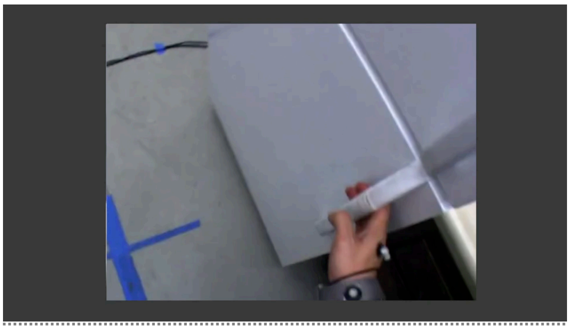
Walterio Mayol-Cuevas

Object Interactions – the Dilemma



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M Wray et al (2017). Improving Classification by Improving Labelling: Introducing Probabilistic Multi-Label Object Interaction Recognition. Arxiv

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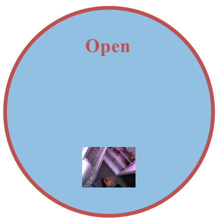
Object Interactions – the Dilemma



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Object Interactions – the Dilemma

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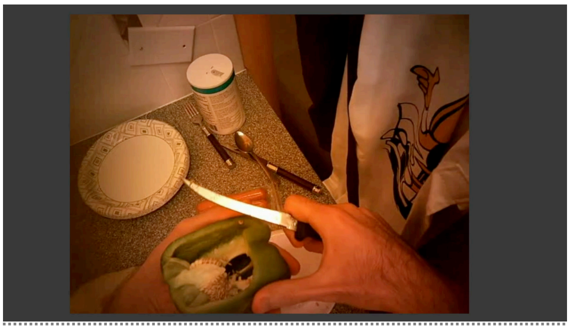

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M Wray et al (2018). Towards an Unequivocal Representation of Actions. Arxiv.
M Wray et al (2017). Improving Classification by Improving Labelling: Introducing Probabilistic Multi-Label Object Interaction Recognition. Arxiv

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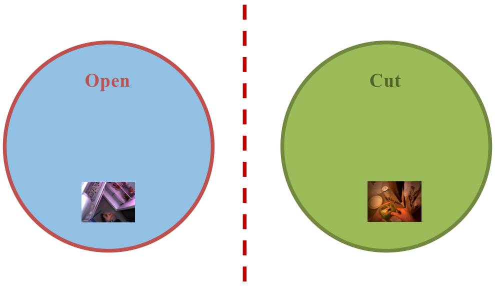
Object Interactions – the Dilemma

with: Michael Wray
Davide Moltisanti
Walterio Mayol-Cuevas



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M Wray et al (2018). Towards an Unequivocal Representation of Actions. Arxiv.
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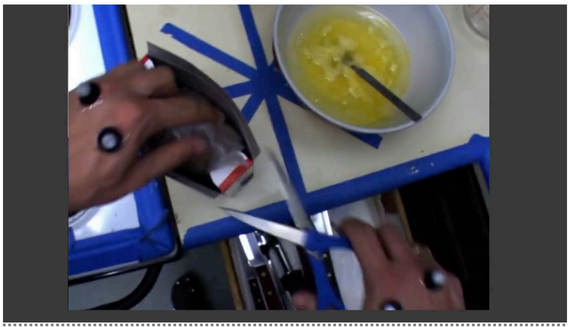
Object Interactions – the Dilemma

with: Michael Wray
Davide Moltisanti
Walterio Mayol-Cuevas



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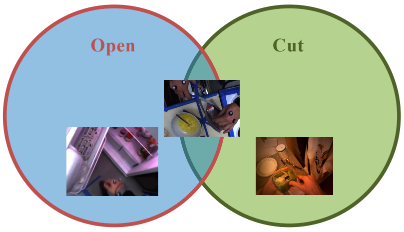
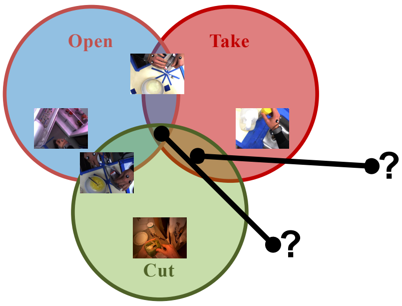
Object Interactions – the Dilemma

with: Michael Wray
Davide Moltisanti
Walterio Mayol-Cuevas



Object Interactions – the Dilemma

with: Michael Wray
Davide Moltisanti
Walterio Mayol-Cuevas



Object Interactions – the Dilemma

with: Michael Wray
Davide Moltisanti
Walterio Mayol-Cuevas

- Verbs cannot be separated into classes with hard boundaries.
- Rather the boundaries are more nuanced – what is correct in one video is incorrect for another.
- Singular classes are not enough.

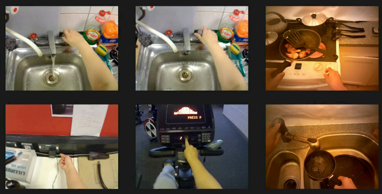
Towards an Unequivocal Representation of Actions

with: Michael Wray
Davide Moltisanti

Top 3 retrieved classes across all datasets.

Turn On/Off
Press
Rotate

Turn On/Off
Press
Rotate



Labelling Method can differentiate turn On/Off tap by pressing and by rotating.

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M Wray et al (2018). Towards an Unequivocal Representation of Actions. Arxiv.
M Wray et al (2017). Improving Classification by Improving Labelling: Introducing Probabilistic Multi-Label Object Interaction Recognition. Arxiv

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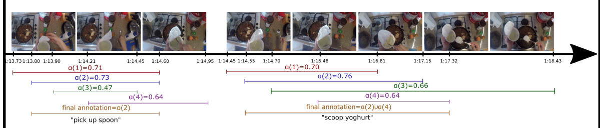
Temporal Boundaries for Object Interactions



- How robust are current state-of-the-art approaches to annotated boundaries in test segments?
- Modify test segment boundaries, maintaining significant overlap of segments IoU > 0.5
- **Correct in Green** – **Incorrect in Red**

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D Moltisanti et al (2017). Trespassing the Boundaries: Labeling Temporal Bounds for Object Interactions in Egocentric Video. *International Conference on Computer Vision (ICCV)*

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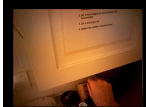
Trespassing the Boundaries

with: Davide Moltisanti
Michael Wray

GTEA Gaze+

ground truth



predicted class: take knife

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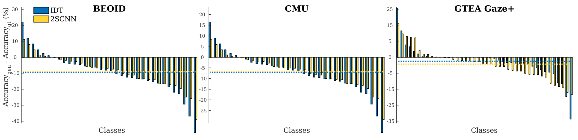
with: Davide Moltisanti
Michael Wray

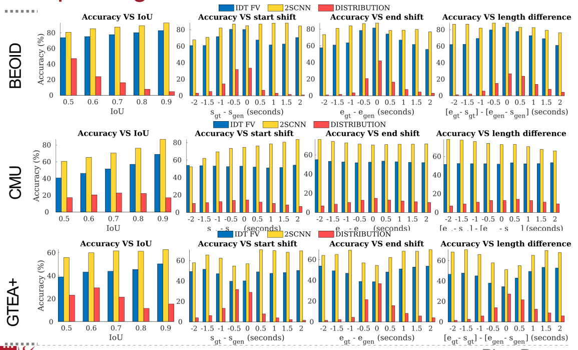
Trespassing the Boundaries



Action

with: Davide Moltisanti
Michael Wray
Walterio Mayol-Cuevas

Trespassing the Boundaries



Action

with: Davide Moltisanti
Michael Wray
Walterio Mayol-Cuevas

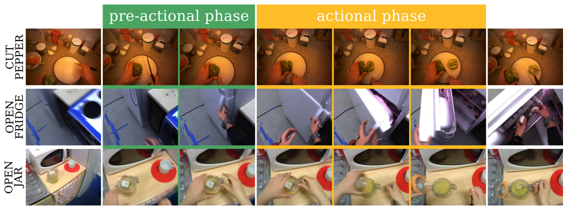
The Rubicon Boundaries

- Labelling approach proposal for temporally consistent annotations
- Decomposes an object interaction into two phases:
  - *pre-actional* phase
  - *actional* phase

Action

The Rubicon Boundaries

with: Davide Moltisanti
Michael Wray
Walterio Mayol-Cuevas



Action

The Rubicon Boundaries

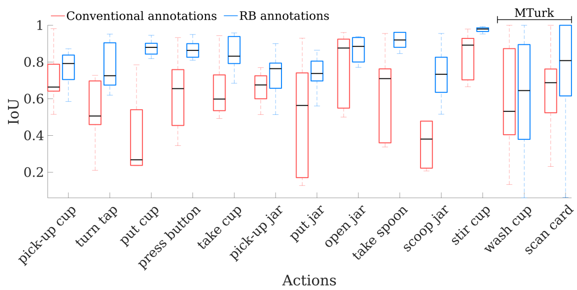
with: Davide Moltisanti
Michael Wray
Walterio Mayol-Cuevas

Cut pepper (GTEA Gaze+)

Action

The Rubicon Boundaries

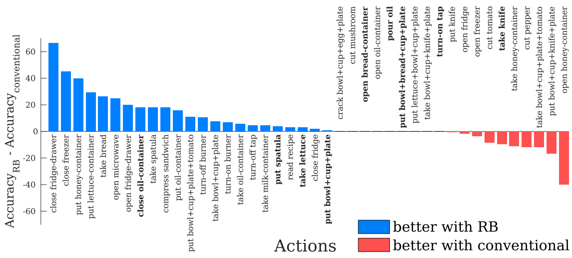
with: Davide Moltisanti
Michael Wray
Walterio Mayol-Cuevas



Action

with: Davide Moltisanti
Michael Wray
Walterio Mayol-Cuevas

The Rubicon Boundaries



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D Moltisanti et al (2017). Trespassing the Boundaries: Labeling Temporal Bounds for Object Interactions in Egocentric Video. *International Conference on Computer Vision (ICCV)*

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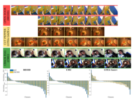
More info…

Project Trespassing the Boundaries of Object Interactions



Video

Trespassing the Boundaries: Labeling Temporal Bounds for Object Interactions in Egocentric Video. D Moltisanti, M Wray, W Mayol-Cuevas, D Damen. International Conference on Computer Vision (ICCV), 2017. pdf (camera ready) | arxiv

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D Moltisanti et al (2017). Trespassing the Boundaries: Labeling Temporal Bounds for Object Interactions in Egocentric Video. *International Conference on Computer Vision (ICCV)*

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with: Will Price

Visualising Learnt Models

- BEOID EBP videos:
- http://youtu.be/4cZS39c7IL0

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The Unique Problems

5. Multi-View Action Recognition

FPV with SPV

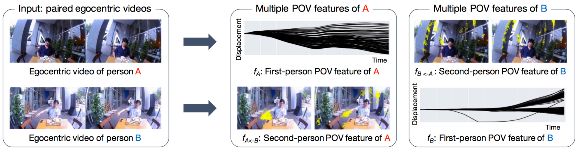

Figure from: Yonetani et al (2016). Recognizing Micro-Actions and Reactions From Paired Egocentric Videos. CVPR

FPV with TPV (top-view)

Figure from: Ardeshir and Borji (2016). Egocentric Meets Top-view CVPR

FPV with TPV (top-view)

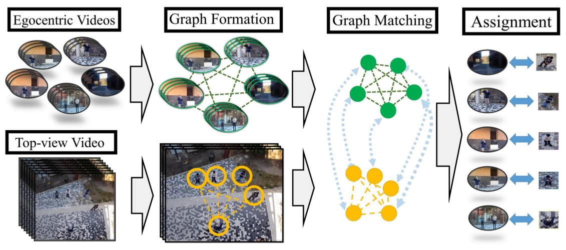

Figure from: Ardeshir and Borji (2016). Ego2Top: Matching Viewers in Egocentric and Top-view Videos. ECCV

Egocentric Vision

- The Unique Problems
  1. Camera Motion
  2. Mapping and Localisation (ref tomorrow's talk)
  3. Attention and Task-Relevance
  4. Object Interactions
  5. Multi-view Solutions
- The Unique Applications
  1. Video Summarisation
  2. Skill Determination
  3. Real-time solutions

The Unique Applications

1. Video Summarisation

Video Summarisation

- Fixations
- Highlight Detection

Egocentric Video Summarisation

- Object-Driven

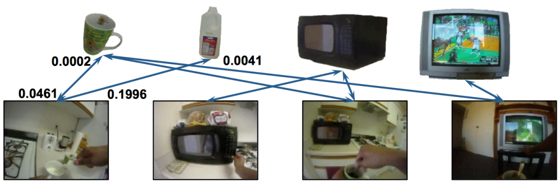

Figure from: Lu and Grauman (2013). Story-Driven Summarization for Egocentric Video. CVPR

Egocentric Video Summarisation

- Object-Driven

Figure from: Lu and Grauman (2013). Story-Driven Summarization for Egocentric Video. CVPR

Egocentric Video Summarisation

- Fixation-Driven with Constraints

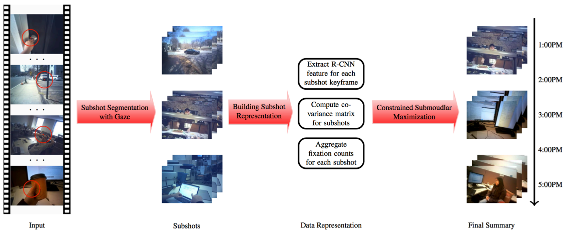

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Figure from: Xu et al (2015). Gaze-enabled Egocentric Video Summarization via Constrained Submodular Maximization . CVPR

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Egocentric Video Summarisation

- Fixations from IMUs

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T Leelasawassuk, D Damen, W Mayol-Cuevas (2015). Estimating Visual Attention from a Head Mounted IMU. International Symposium on Wearable Computers (ISWC)

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The Unique Applications

2. Skill Determination

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Who's Better? Who's Best? Skill Determination in Video using Deep Ranking

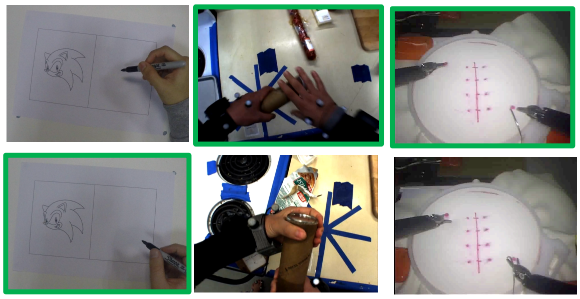
with: Hazel Doughty
Walterio Mayol-Cuevas

Assess relative skill for a collection of video sequences, applicable to a variety of tasks.

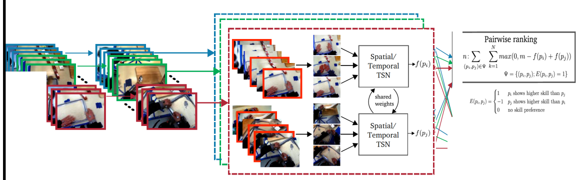
Who's Better? Who's Best? Skill Determination in Video using Deep Ranking

with: Hazel Doughty
Walterio Mayol-Cuevas

Input: Pairwise annotations of videos, indicating higher skill or no skill preference



Who's Better? Who's Best? Skill Determination in Video using Deep Ranking



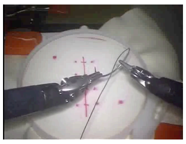
Video 1 ~ Video 2

Who's Better? Who's Best? Skill Determination in Video using Deep Ranking

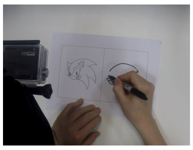
with: Hazel Doughty
Walterio Mayol-Cuevas

EPIC-SKILLS 2018

Surgery[1]



Drawing



Dough-Rolling[2]

Chopstick-Using

[1] Gao, Yixin, et al. "The JHU-ISI gesture and skill assessment dataset (JIGSAWS): A surgical activity working set for human motion modeling." Medical Image Computing and Computer-Assisted Intervention (MICCAI). 2014.

[2] De la Torre, Fernando, et al. "Guide to the carnegie mellon university multimodal activity (CMU-MMAC) database." *Robotics Institute* (2008): 135.

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Who's Better? Who's Best? Skill Determination in Video using Deep Ranking

with: Hazel Doughty
Walterio Mayol-Cuevas

$$L_{rank1} = \sum_{(p_i,p_j)\in\Psi} max(0, m - f(p_i) + f(p_j)) \quad (3)$$

$$L_{rank2} = \sum_{(p_i,p_j)\in\Psi} \sum_{k=1}^{N} max(0, m - f_k(p_i) + f_k(p_j)) \quad (5)$$

$$L_{sim} = \sum_{(p_i,p_j)\in\Phi} \sum_{k=1}^{N} max(0, |f(p_i) - f(p_j)| - m) \quad (7)$$

$$L_{rank3} = \beta L_{rank2} + (1 - \beta) L_{sim} \quad (8)$$

Method	Surgery			Dough-Rolling			Drawing			Chopstick-Using		
	S	T	TS	S	T	TS	S	T	TS	S	T	TS
Siamese TSN with margin loss	64.7	72.8	69.1	77.6	79.4	78.5	75.6	77.4	78.0	67.2	67.9	68.8
+ splits	64.4	**73.3**	69.0	79.1	**80.4**	78.5	74.9	81.8	79.1	67.2	69.9	68.8
+ similarity loss	**66.4**	72.5	**70.2**	**79.5**	79.5	**79.4**	**77.6**	**82.7**	**83.2**	**70.8**	**70.6**	**71.5**

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H Doughty, D Damen, W Mayol-Cuevas (2018). Who's Better? Who's Best? Pairwise Deep Ranking for Skill Determination. CVPR

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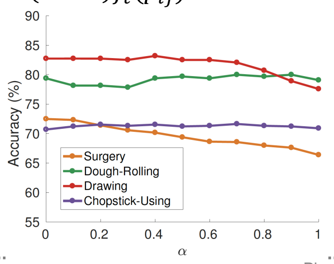
Who's Better? Who's Best? Skill Determination in Video using Deep Ranking

with: Hazel Doughty
Walterio Mayol-Cuevas

$$\frac{1}{\sigma}\sum_{j=1}^{\sigma} \alpha f_s(p_{ij}) + (1-\alpha) f_t(p_{ij})$$



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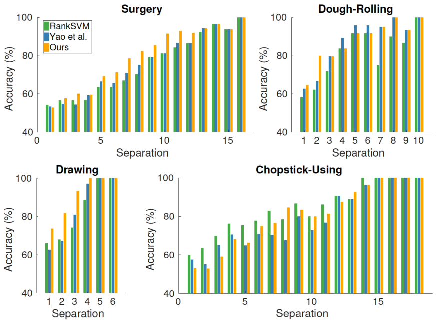

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H Doughty, D Damen, W Mayol-Cuevas (2018). Who's Better? Who's Best? Pairwise Deep Ranking for Skill Determination. CVPR

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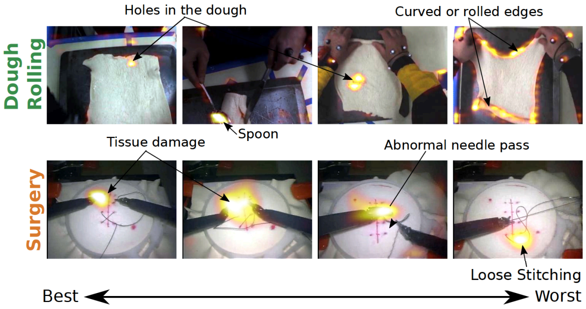
Who’s Better? Who’s Best? Skill Determination in Video using Deep Ranking

with: Hazel Doughty
Walterio Mayol-Cuevas



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H Doughty, D Damen, W Mayol-Cuevas (2018). Who's Better? Who's Best? Pairwise Deep Ranking for Skill Determination. CVPR

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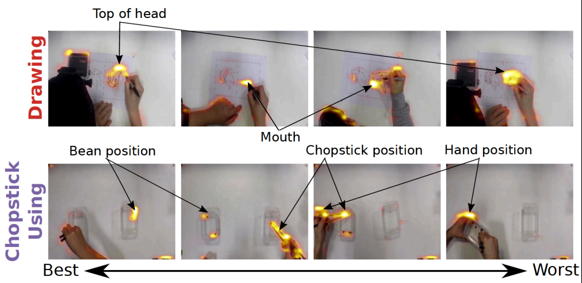
Who’s Better? Who’s Best? Skill Determination in Video using Deep Ranking

with: Hazel Doughty
Walterio Mayol-Cuevas



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H Doughty, D Damen, W Mayol-Cuevas (2018). Who's Better? Who's Best? Pairwise Deep Ranking for Skill Determination. CVPR

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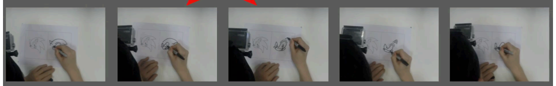
with: Hazel Doughty
Walterio Mayol-Cuevas

Example Rankings



Sonic-Drawing task - part of new skill dataset

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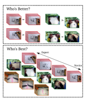
More info…

Project Who's Better, Who's Best: Skill Determination in Video



Video

Who's Better? Who's Best? Pairwise Deep Ranking for Skill Determination. H Doughty, D Damen, W Mayol-Cuevas. CVPR (2018). PDF | arxiv

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The Unique Applications

3. Real-time Solutions

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Wearable (Systems)!

- On-the-cloud processing
- On-the-mobile processing
- Onboard processing!

Connecting-to-the-cloud

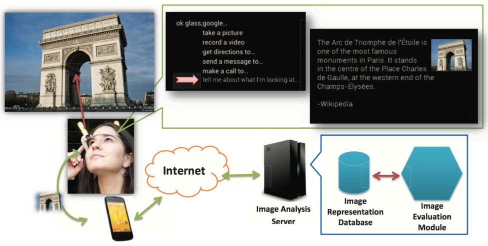

Figure 1. System overview. The user asks the device to inform her about her current view of Arc de Triomphe, and the system responds with the most relevant description in its database.

Altwaijry et al (2014). Recognizing locations with Google Glass: A case study. WACV

Action

with: Walterio Mayol-Cuevas
Teesid Leelasawassuk

You Do, I Learn – Google Glass Prototype

D Damen, T Leelasawassuk, W Mayol-Cuevas (2016). You-Do, I-Learn: Egocentric Unsupervised Discovery of Objects and their Modes of Interaction Towards Video-Based Guidance. *Computer Vision and Image Understanding*

The need for large-scaled datasets…

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EPIC KITCHENS

with: Hazel Doughty
Giovanni Maria Farinella
Sanja Fidler
Antonino Furnari
Evangelos Kazakos
Davide Moltisanti
Jonathan Munro
Toby Perrett
Will Price
Michael Wray

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D Damen et al (2018). Scaling Egocentric Vision: The EPIC-KITCHENS Dataset. Arxiv. https://epic-kitchens.github.io

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Davide Moltisanti
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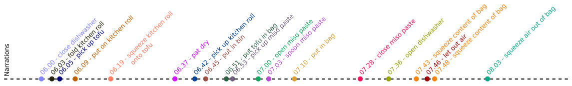
Will Price
Michael Wray



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Jonathan Munro
Toby Perrett
Will Price
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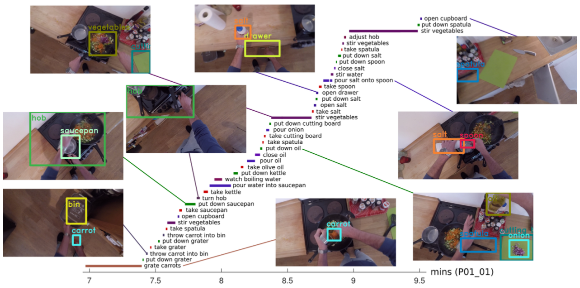

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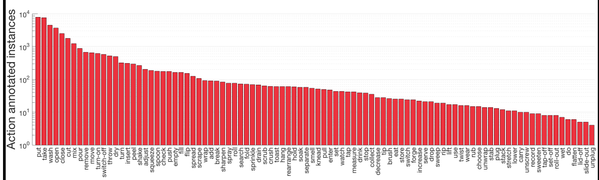

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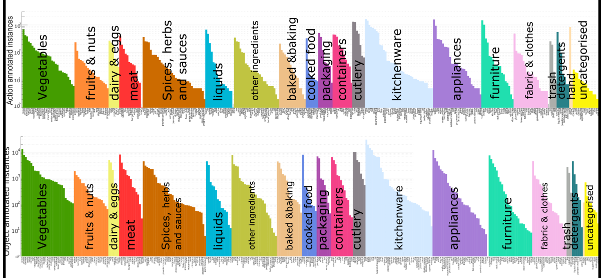

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EPIC KITCHENS

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Davide Moltisanti
Jonathan Munro
Toby Perrett
Will Price
Michael Wray

TABLE 1: Comparative overview of relevant datasets. *action classes with > 50 samples

Dataset	Ego?	Non-Scripted?	Native Env?	Year	Frames	Sequ-ences	Action Segments	Action Classes	Object BBs	Object Classes	Partici-pants	No. Env.s
EPIC-KITCHENS	✓	✓	✓	2018	11.5M	432	39,596	149*	454,158	323	32	32
EGTEA Gaze+ [19]	✓	×	×	2018	2.4M	86	10,325	106	0	0	32	1
BEOID [21]	✓	×	×	2014	0.1M	58	1,488	34	0	0	5	1
GTEA Gaze+ [20]	✓	×	×	2012	0.4M	35	3,371	42	0	0	13	1
ADL [23]	✓	×	✓	2012	1.0M	20	436	32	137,780	42	20	20
CMU [22]	✓	×	×	2009	0.2M	16	516	31	0	0	16	1
VLOG [15]	×	✓	✓	2017	37.2M	114K	0	0	0	0	10.7K	N/A
Charades [16]	×	×	✓	2016	7.4M	9,848	67,000	157	0	0	N/A	267
Breakfast [24]	×	✓	✓	2014	3.0M	433	3078	50	0	0	52	18
50 Salads [25]	×	×	×	2013	0.6M	50	2967	52	0	0	25	1
MPII Cooking 2 [26]	×	×	×	2012	2.9M	273	14,105	88	0	0	30	1

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TABLE 4: Statistics of test splits: seen (S1) and unseen (S2) kitchens

	#Subjects	#Sequences	Duration (s)	%	Narrated Segments	Action Segments	Bounding Boxes
Train/Val	28	272	141731		28,588	28,561	326,298
S1 Test	28	106	39084	20%	8,069	8,064	97,865
S2 Test	4	54	13231	7%	2,939	2,939	29,995

		15 Most Frequent Object Classes															Totals		
	mAP	pan	plate	bowl	onion	tap	pot	knife	spoon	meat	food	potato	cup	pasta	cupboard	lid	few-shot	many-shot	all
S1	IoU > 0.05	74.00	72.61	71.50	60.72	84.44	69.97	44.03	40.93	29.65	58.52	62.82	53.30	78.39	51.95	62.77	9.71	49.80	38.23
	IoU > 0.5	67.60	66.21	65.98	39.96	73.80	64.71	28.80	23.89	20.75	49.85	55.48	42.99	69.75	29.20	58.48	6.98	36.50	28.06
	IoU > 0.75	21.94	44.60	39.48	3.52	25.83	19.67	3.42	2.59	5.27	15.78	13.18	8.00	24.53	4.05	26.51	0.36	8.73	6.50
S2	IoU > 0.05	75.94	87.36	72.72	47.61	78.14	75.92	55.51	41.28	71.59	38.61	N/A	44.62	80.58	53.88	58.40	6.00	51.71	40.61
	IoU > 0.5	62.88	84.86	68.61	32.18	59.75	62.86	39.60	27.52	53.54	35.47	N/A	39.19	76.27	32.54	49.36	5.32	36.27	28.57
	IoU > 0.75	14.56	62.82	38.44	2.25	4.89	14.91	3.85	1.51	9.56	8.10	N/A	7.60	43.30	5.61	25.48	0.18	9.05	7.04

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TABLE 6: Baseline results for the action recognition challenge

		Top-1 Accuracy			Top-5 Accuracy			Avg Class Precision			Avg Class Recall		
		VERB	NOUN	ACTION	VERB	NOUN	ACTION	VERB	NOUN	ACTION	VERB	NOUN	ACTION
S1	RGB	45.25	35.78	18.91	**86.07**	**62.80**	**39.39**	54.94	40.41	07.01	**23.31**	**30.03**	**05.29**
	FLOW	43.27	17.92	09.10	79.89	39.63	21.91	**64.58**	24.51	01.52	15.35	09.72	01.28
	FUSION	**47.36**	**36.05**	**19.44**	84.27	61.05	35.45	63.12	**44.24**	**07.33**	21.95	29.25	05.22
S2	RGB	35.96	21.74	09.96	**74.70**	44.95	**24.59**	45.40	22.14	02.06	11.79	16.75	**01.91**
	FLOW	**40.56**	14.91	07.28	73.66	33.87	18.29	44.83	22.99	00.92	**14.16**	08.79	00.94
	FUSION	39.67	**22.33**	**10.84**	74.53	**45.23**	23.52	**59.60**	**23.65**	**02.09**	13.37	**16.84**	01.84

TABLE 7: Sample baseline action recognition per-class metrics (using fusion)

		15 Most Frequent Verb Classes														
		put	take	wash	open	close	cut	mix	pour	move	turn-on	remove	turn-off	throw	dry	peel
S1	RECALL	65.32	51.01	80.45	60.98	27.13	74.27	52.63	24.87	00.00	05.63	01.58	03.67	10.11	29.73	26.09
	PRECISION	35.62	41.24	63.17	72.67	72.46	69.38	69.52	66.20	-	53.33	66.67	50.00	56.25	88.00	54.55
S2	RECALL	64.16	48.03	87.76	42.06	15.10	45.69	35.85	06.06	00.00	00.00	00.81	00.00	00.00	00.00	00.00
	PRECISION	30.19	30.46	67.79	57.31	61.54	85.48	65.52	40.00	-	00.00	100.0	-	-	-	00.00

Interactive Conclusions

- Fill in the blanks:
  - Egocentric vision is ---------------------
  - Pick up an action (e.g. open door). Draw a sketch of how it looks like from FPV and TPV
  - The biggest challenge (in your opinion) in egocentric vision is ---------------------------------
  - The most interesting problem (to you) in egocentric vision is -----------------------------------

Interested in More?

- Egocentric Perception, Interaction and Computing (EPIC) Workshop Series
  - ECCV 2016 (Amsterdam)
  - ICCV 2017 (Venice)
  - ECCV 2018 (Munich)
    - Paper deadline: Tomorrow!
    - Abstract submission till 23rd of July (ongoing work)

Interested in More?

- Subscribe to the newly introduced mailing list: epic-community@bristol.ac.uk
- Instructions to subscribe:
  - send an email to: sympa@sympa.bristol.ac.uk
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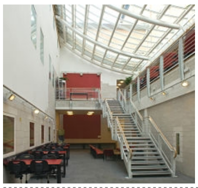

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Thank you…

For further info, datasets, code, publications…

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