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A Fine-grained Perspective onto Object Interactions from First-person Views

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Abstract: This extended abstract summarises the relevant works to the keynote lecture at VISAPP 2019. The talk discusses understanding object interactions from wearable cameras, focusing on fine-grained understanding of interactions on realistic unbalanced datasets recorded in-the-wild.

1 INTRODUCTION

Humans interact with tens of objects daily, at home (e.g. cooking/cleaning), during working (e.g. assembly/machinery) or leisure hours (e.g. playing/sports), individually or collaboratively. The field of research, within computer vision and machine learning, that focuses on the perception of object interactions from a wearable cameras is commonly referred to as ‘first-person vision’. In this extended abstract, we cover novel research questions, particularly related to the newly released largest dataset in object interactions, recorded in people’s native environments: EPIC-Kitchens.

2 Definitions

Object interactions could be perceived from different ordinal-person viewpoints - where ‘ordinal’ is used to generalise between *first-*, *second-* and *third-* person views. A view is referred to as a first-person view, if the interaction is captured by a wearable sensor, worn by the actor performing the interaction itself. Conversely, a second-person view is when the interaction is captured by a camera of a co-actor, or a recipient of the action. Finally, a third-person view, common in remote static cameras, is when the interaction is captured by an observer not relevant to the interaction or the actor during that interaction.

3 Datasets and EPIC-Kitchens

For years, Computer Vision has focused on capturing videos from a third-person view, with the majority of action recognition datasets using a remote camera observing the action or interaction (Marszalek et al., 2009; Kuehne et al., 2011; Caba Heilbron et al., 2015; Carreira and Zisserman, 2017).

Increasingly, first-person vision datasets have been recorded, capturing full body motion such as sports (Kitani et al., 2011), social interactions (Alletto et al., 2015; Fathi et al., 2012a; Ryoo and Matthies, 2013) and object interactions (De La Torre et al., 2008; Fathi et al., 2012b; Pirsiavash and Ramanan, 2012; Damen et al., 2014; Georgia Tech, 2018; Sigurdsson et al., 2018).

In 2018, the largest dataset on wearable cameras was released through a collaboration led by the University of Bristol alongside the University of Catania and the University of Toronto - <http://epic-kitchens.github.io/>. EPIC-Kitchens (Damen et al., 2018) offers more than 11.5M frames, captured using a head-mounted camera in 32 different kitchens, with over 55 hours of natural interactions from cooking to washing the dishes (Fig 1).

4 Fine-Grained Object Interactions

Datasets, such as EPIC-Kitchens, can offer unique opportunities to studying previously unexplored prob-


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Figure 1: Sample frames from EPIC-Kitchens

lems in fine-grained object interactions. A few of these opportunities are highlighted here.

- *Overlapping Object Interactions:* Defining the temporal extent of an action is fundamentally an ambiguous problem (Moltisanti et al., 2017; Sigurdsson et al., 2017). This is usually resolved through multi-labels, i.e. allowing a time-segment to belong to multiple classes of actions. However, actual understanding of interaction overlapping requires an space of action labels that captures dependencies (e.g. filling a kettle requires opening the tap). Models that capture and predict overlapping interactions are needed for a finer-understanding of object interactions.
- *Object Interaction Completion/Incompletion:* Beyond classification and localisation, action completion/incompletion is the problem of identifying whether the action’s goal has been successfully achieved, or merely attempted. This is a novel fine-grained object interaction research question proposed in (Heidarvincheh et al., 2016). This work has been recently extended to locating the moment of completion (Heidarvincheh et al., 2018) - that is the moment in time beyond which the action’s goal is believed to be completed by a human observer.
- *Skill Determination from Video:* Even when an interaction is successfully completed, further understanding of ‘how well’ the task was completed would offer knowledge beyond pure classification. In this leading work (Doughty et al., 2018a), a collection of video could be ordered by the skill exhibited in each video, through deep pairwise ranking. This method has been recently extended to include rank-aware attention (Doughty et al., 2018b) - that is a novel loss function capable of attending to parts of the video that exhibit higher skill as well as parts that demonstrate lower skill including mistakes or hesitation.
- *Anticipation and Forecasting:* Predicting upcoming

interactions has recently gathered additional attention, triggered by the presence of first-person datasets (Furnari et al., 2018; Rhinehart and Kitani, 2017). Novel research on uncertainty in anticipating actions (Furnari et al., 2018), or relating forecasting to trajectory prediction (Rhinehart and Kitani, 2017) have recently been proposed.

- *Paired Interactions:* One leading work has attempted capturing both the action and its counteraction (or reaction), both from a wearable camera (Yonetani et al., 2016). This is a very exciting area of research, still under-explored.

5 Conclusion

Recent deep-learning research has only scratched the surface of potentials for finer-grained understanding of object interactions. As new hardware platforms for first-person vision emerge (Microsoft’s HoloLens, Magic Leap, Samsung Gear, ...), applications of fine-grained recognition will be endless.

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