Enabling Tangible Interaction through Detection and Augmentation of Everyday Objects

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Abstract
Digital interaction with everyday objects has become popular since the proliferation of camera-based systems that detect and augment objects "just-in-time". Common systems use a vision-based approach to detect objects and display their functionalities to the user. Sensors, such as color and depth cameras, have become inexpensive and allow seamless environmental tracking in mobile as well as stationary settings. However, object detection in different contexts faces challenges as it highly depends on environmental parameters and the conditions of the object itself. In this work, we present three tracking algorithms which we have employed in past research projects to track and recognize objects. We show, how mobile and stationary augmented reality can be used to extend the functionalities of objects. We conclude, how common items can provide user-defined tangible interaction beyond their regular functionality.

Author Keywords
Object Tracking; Computer Vision; In-Situ Assistance; Assistive Systems; Workload-Aware Interfaces

ACM Classification Keywords
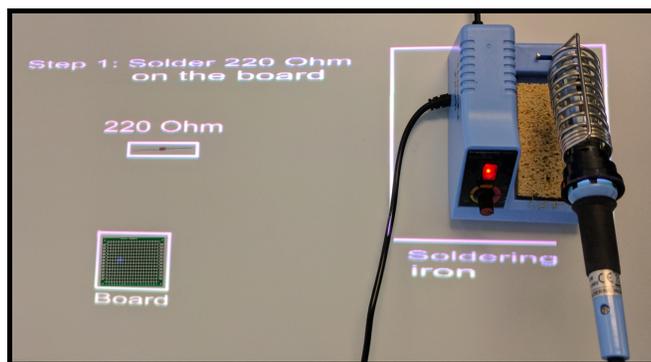H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Figure 1: Augmented workspace in the context of electrical engineering. In-situ projections augment and trace objects as well as track user actions.

Introduction

Augmenting common items with digitized content to extend their functionalities has been the focus of past research in the domain of tangible user interfaces [9]. Thereby, objects are tracked by a system that displays visual cues or extends the functionality of the object itself [10]. By rotating, repositioning, or placing objects in defined positions, user-defined actions can be triggered. Thus, common items are augmented by functionalities which they do not implement by themselves.

Two modalities to display such augmented content have emerged. Smart glasses, such as the Microsoft HoloLens[1], enable mobile use of augmented reality to display additional supporting content [4]. Furthermore, in-situ projection systems enable the augmentation of stationary workstations that can be used for practical exercises (see Figure 1). While smart glasses are preferred in a mobile context, in-situ projections are suitable for stationary settings. While mobile augmentation was preferred during practical physics exercises that required mobility of their students [18], industrial use cases [5] and social housing organizations [14, 15] found stationary settings more suitable. Furthermore, employing object augmentation provides cognitive alleviation, which has the potential to boost overall user performance and productivity [11, 12].

Both modalities use camera-based systems to recognize objects and enrich them with additional content. However, seamless object detection and augmentation poses challenges for different use cases. In this work, we present object detection strategies we employed in past research projects to enable object detection and augmentation. We discuss the advantages and disadvantages of different
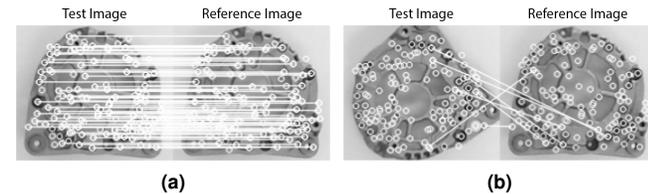
Figure 2: Object detection using SURF. The positioned object is compared to a reference image. Feature extraction, such as provided by the SURF algorithm, shows the similarity of the image. **(a):** Correct positioned image. **(b):** A rotated object does not guarantee that it will be detected relative to the reference image.

object tracking modalities. Finally, we present how user-defined tangibles from everyday items can be created by augmenting them with in-situ projections. We conclude with challenges that have to be considered when integrating ubiquitous object augmentation.

Object Tracking

To enable interaction with common items, suitable tracking systems and algorithms need to be employed. In the following, we present three object tracking strategies we have employed in past research.

SURF

The Speeded Up Robust Feature (SURF) algorithm [3] enables to recognize points and areas of "interest" in images. Due to its efficient implementation, it enables the processing of images in real-time. Thereby, the algorithm has been used for object detection by comparing points of interest in a captured image relative to a reference image [2]. SURF can be employed with inexpensive hardware since it processes color images. However, SURF is not rotation and
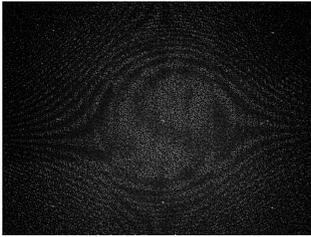
Figure 3: Infrared pattern of a Kinect v1 on a wooden plate [1].

perspective invariant. This requires objects to be in a similar position that is expected by a system (see Figure 2).

Depth Sensing
A depth sensor, such as the Intel Realsense[2] or the Kinect v2[3], provide a 3D representation of objects that they are pointed to. Objects are recognized by analyzing the shape. Thereby, two relevant methods have emerged. The first method uses a projected infrared pattern on a surface (see Figure 3). Afterward, the depth sensor measures changes in the perspective of the pattern. This enables to detect the distance between infrared waves and allows a reconstruction of the 3D space on a surface [1]. The second method uses a Time-of-Flight approach. Thereby, the round trip time of an artificial light (i.e., infrared light) is measured between the sensor and a point on the surface. When the reflection of the light is captured, a 3D representation on of the surface is created [8].

Depth sensing is insensitive to lighting conditions. However, changes in perspective and rotation of objects may affect the overall detection quality. Thus, depth sensing is suitable for use cases where objects reside in stable positions.

You Only Look Once
The algorithm "You Only Look Once" (YOLO) is a deep learning approach to detect objects regardless of their perspective and position [17] (see Figure 4). It applies a single neural network on an image that detects features in bounding boxes after clustering their properties. By evaluating those properties, a probability of a correctly detected object is calculated. While YOLO represents a robust real-time method to detect objects regardless of their positioning and

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[2]www.intel.com/content/www/us/en/architecture-and-technology/realsense-overview.html - last access 2019-05-17
[3]https://developer.microsoft.com/en-us/windows/kinect - last access 2019-05-17
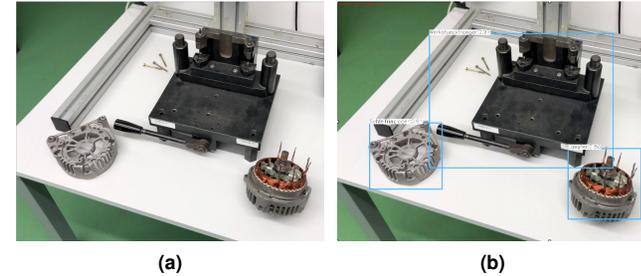

(a)   **(b)**

Figure 4: Using YOLO to detect objects independent from their position. **(a):** Test image to evaluate a trained model. **(b):** Detected objects using YOLO. A blue bounding box denotes the detected objects.

perspective, it requires an extensive training set beforehand. Furthermore, training a neural network on a large data set requires time and, depending on the use case, fast computational hardware to speed up the training process.

Object Augmentation
Objects can be used as a visual cue for interaction or interaction device itself. In the following, we show implementations of tangible object augmentation we have conducted in the past.

Ambient Augmentation
After recognizing the type of object, cues can be used to implicitly guide the user through a series of actions. Figure 5 shows an augmented workspace that uses in-situ projection as a guide through a series of assembly steps. By detecting the user's action and items on the workspace, in-situ projections are placed on the current relevant bin or final spot for assembly. While boosting the overall performance of workers in industrial environments [7], people with
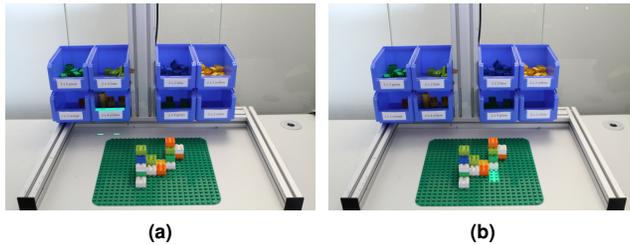
(a)   **(b)**

Figure 5: Augmenting a workplace using in-situ projections. **(a):** A detected item selection bin is visually highlighted. **(b):** A projection on the working area depicts the final position of an assembly part.

dementia and loss in memory benefit from in-situ projections [13].

User-defined Tangibles

Regular objects can be registered as user-defined tangible that is made available for interaction [6]. For example, rotating (see Figure 6a) or positioning (see Figure 6b) objects can be used to change the speaker volume.

After registering the object, a series of options are made available to the user. The user can choose to interact with existing objects or register new objects. Such objects can be everyday items which do not implement a logic. This transforms objects into user-defined tangibles that are already around the user with just-in-time interaction.

Challenges and Future Work

Seamless object detection and augmentation in home and workplace settings are prone to certain challenges. In this work, we presented three strategies to detect objects and augment objects. However, choosing the right detection modality depends on the environment as well as on the properties of the object itself. For example, a depth sen-
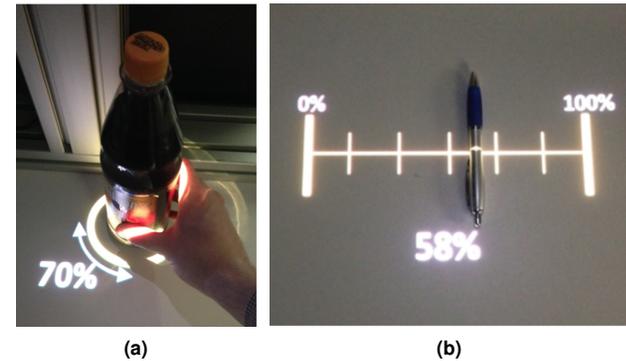

(a)   **(b)**

Figure 6: User-defined tangibles that use in-situ projections to provide feedback. **(a):** Rotating a bottle similar to a knob. **(b):** Using a pen as a slider [6].

sor will struggle to detect flat objects as they have scarce 3D properties. While a regular color camera can solve this problem, it is sensitive to the overall environmental illumination. In future work, we want to combine the definition and detection of user-defined tangibles by using an approach that combines color as well as depth images [16]. Thereby, a combination of depth and color data provides an approximation of object type.

Furthermore, privacy and ethical considerations have to be taken into account. By using the presented camera-based approach, public and private spaces are recorded during user interaction. While users can give consent to process the collected data in private settings, public spaces and workplaces are more sensitive to privacy-related issues. In future work, we want to investigate those ethical ramifications. Ultimately, we will investigate design guidelines that explore how a camera-based approach can be conducted while minimally invading the user's privacy.

Conclusion

In this work, we present three strategies to detect objects which we have employed in past research projects. We outline the advantages and disadvantages of each strategy which we have encountered. We show how object detection and user-defined tangibles can be implemented to provide ambient or explicit interaction. Finally, we discuss challenges that have to be tackled before enabling seamless object tracking in home and work settings. Since common objects do not implement any logic, we believe that external object augmentation paves the way for ubiquitous tangible interaction at home, public spaces, and workplaces.

REFERENCES

1. Michael Riis Andersen, Thomas Jensen, Pavel Lisouski, Anders Krogh Mortensen, Mikkel Kragh Hansen, Torben Gregersen, and Peter Ahrendt. 2012. Kinect depth sensor evaluation for computer vision applications. *Aarhus University* (2012), 1–37.

2. Herbert Bay, Tinne Tuytelaars, and Luc Van Gool. 2006. SURF: Speeded Up Robust Features. In *Computer Vision – ECCV 2006*, Aleš Leonardis, Horst Bischof, and Axel Pinz (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 404–417.

3. Dimitris Bouris, Antonis Nikitakis, and Ioannis Papaefstathiou. 2010. Fast and Efficient FPGA-Based Feature Detection Employing the SURF Algorithm. In *2010 18th IEEE Annual International Symposium on Field-Programmable Custom Computing Machines*. 3–10. DOI:http://dx.doi.org/10.1109/FCCM.2010.11

4. Wilhelm Dangelmaier, Matthias Fischer, Jürgen Gausemeier, Michael Grafe, Carsten Matysczok, and Bengt Mueck. 2005. Virtual and augmented reality support for discrete manufacturing system simulation. *Computers in Industry* 56, 4 (2005), 371 – 383. DOI:http://dx.doi.org/https://doi.org/10.1016/j.compind.2005.01.007 The Digital Factory: An Instrument of the Present and the Future.

5. Markus Funk, Andreas Bächler, Liane Bächler, Thomas Kosch, Thomas Heidenreich, and Albrecht Schmidt. 2017. Working with Augmented Reality? A Long-Term Analysis of In-Situ Instructions at the Assembly Workplace. In *Proceedings of the 10th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, New York, NY, USA. DOI:http://dx.doi.org/10.1145/3056540.3056548

6. Markus Funk, Oliver Korn, and Albrecht Schmidt. 2014. An Augmented Workplace for Enabling User-Defined Tangibles. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems (CHI EA'14)*. ACM, New York, NY, USA, 1285–1290. DOI:http://dx.doi.org/10.1145/2559206.2581142

7. Markus Funk, Thomas Kosch, and Albrecht Schmidt. 2016. Interactive Worker Assistance: Comparing the Effects of In-situ Projection, Head-mounted Displays, Tablet, and Paper Instructions. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (2016), 934–939. DOI:http://dx.doi.org/10.1145/2971648.2971706

8. Burak Gokturk, Hakan Yalcin, and Cyrus Bamji. 2004. A Time-Of-Flight Depth Sensor - System Description, Issues and Solutions. In *2004 Conference on Computer Vision and Pattern Recognition Workshop*. 35–35. DOI:http://dx.doi.org/10.1109/CVPR.2004.291

9. Eva Hornecker and Jacob Buur. 2006. Getting a Grip on Tangible Interaction: A Framework on Physical Space and Social Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '06)*. ACM, New York, NY, USA, 437–446. DOI: http://dx.doi.org/10.1145/1124772.1124838

10. Martin Kaltenbrunner and Ross Bencina. 2007. reacTIVision: A Computer-vision Framework for Table-based Tangible Interaction. In *Proceedings of the 1st International Conference on Tangible and Embedded Interaction (TEI '07)*. ACM, New York, NY, USA, 69–74. DOI: http://dx.doi.org/10.1145/1226969.1226983

11. Thomas Kosch, Yomna Abdelrahman, Markus Funk, and Albrecht Schmidt. 2017. One Size does not Fit All - Challenges of Providing Interactive Worker Assistance in Industrial Settings. *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (2017), 6. DOI: http://dx.doi.org/10.1145/3123024.3124395

12. Thomas Kosch, Markus Funk, Albrecht Schmidt, and Lewis Chuang. 2018. Identifying Cognitive Assistance with Mobile Electroencephalography: A Case Study with In-Situ Projections for Manual Assembly. In *Proceedings of the 10th ACM SIGCHI symposium on Engineering interactive computing systems*. ACM. DOI: http://dx.doi.org/10.1145/3229093

13. Thomas Kosch, Romina Kettner, Markus Funk, and Albrecht Schmidt. 2016. Comparing Tactile, Auditory, and Visual Assembly Error-Feedback for Workers with Cognitive Impairments. In *Proceedings of the 18th international ACM SIGACCESS conference on Computers & accessibility*. ACM. DOI: http://dx.doi.org/10.1145/2982142.2982157

14. Thomas Kosch, Kevin Wennrich, Daniel Topp, Marcel Muntzinger, and Albrecht Schmidt. 2019. The Digital Cooking Coach: Using Visual and Auditory In-Situ Instructions to Assist Cognitively Impaired during Cooking. In *Proceedings of the 12th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, New York, NY, USA. DOI:http://dx.doi.org/10.1145/3316782.3321524

15. Thomas Kosch, Pawel Wozniak, Erin Brady, and Albrecht Schmidt. 2018. Smart Kitchens for People with Cognitive Impairments: A Qualitative Study of Design Requirements. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA. DOI: http://dx.doi.org/10.1145/3173574.3173845

16. Kevin Lai, Liefeng Bo, Xiaofeng Ren, and Dieter Fox. 2011. Sparse distance learning for object recognition combining RGB and depth information. In *2011 IEEE International Conference on Robotics and Automation*. 4007–4013. DOI: http://dx.doi.org/10.1109/ICRA.2011.5980377

17. Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. 2016. You Only Look Once: Unified, Real-Time Object Detection. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

18. Martin P. Strzys, Sebastian Kapp, Michael Thees, Pascal Klein, Paul Lukowicz, Pascal Knierim, Albrecht Schmidt, and Jochen Kuhn. 2018. Physics holo.lab learning experience: using smartglasses for augmented reality labwork to foster the concepts of heat conduction. *European Journal of Physics* 39, 3 (mar 2018), 035703. DOI: http://dx.doi.org/10.1088/1361-6404/aaa8fb