

Privacy-Aware and Acceptable Video-Based Technologies and Services for Active and Assisted Living

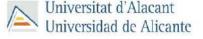
Privacy Preservation in Video-based AAL Applications

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Stockholm, Sweden 20 Apr 2023

2nd Doctoral Seminar













Privacy by Context





Privacy by Context

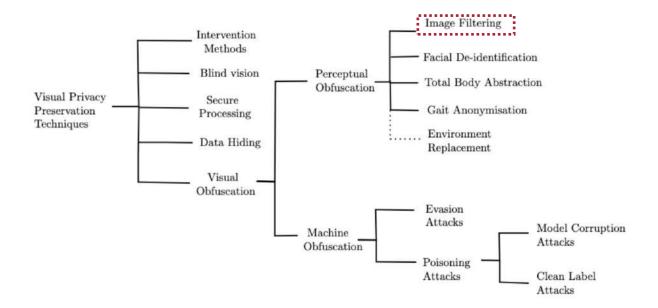








- Created a comprehensive review of visual privacy preservation techniques [1].
 - Proposed a new taxonomy of visual privacy preservation techniques for AAL.



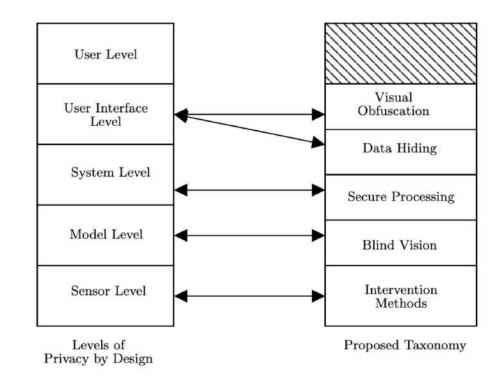
[1] Ravi, S., Climent-Pérez, P., & Florez-Revuelta, F. (2021). A review on visual privacy preservation techniques for active and assisted living. arXiv preprint arXiv:2112.09422.

[2] Mihaildis, A., & Colonna, L. (2020). A methodological approach to privacy by design within the context of lifelogging technologies. Rutgers Computer & Tech. LJ, 46, 1.





- Created a comprehensive review of visual privacy preservation techniques [1].
 - Proposed a new taxonomy of visual privacy preservation techniques for AAL.
 - Created a connection between the taxonomy for privacy by design proposed by Mihailidis and Colonna (2020) [2] and the proposed taxonomy.



[1] Ravi, S., Climent-Pérez, P., & Florez-Revuelta, F. (2021). A review on visual privacy preservation techniques for active and assisted living. *arXiv* preprint arXiv:2112.09422. [2] Mihaildis, A., & Colonna, L. (2020). A methodological approach to privacy by design within the context of lifelogging technologies. *Rutgers Computer & Tech. LJ*, 46, 1.





 Collaborated on studies of fairness of commonlyused visual privacy preservation methods with Sophie Noiret et al. [1, 2]



[1] Noiret, S., Ravi, S., Kampel, M., & Florez-Revuelta, F. (2022, June). On The Nature of Misidentification With Privacy Preserving Algorithms. In *Proceedings of the 15th International Conference on PErvasive Technologies Related to Assistive Environments* (pp. 422-424).

[2] Noiret, S., Ravi, S., Kampel, M., & Florez-Revuelta, F. (2023). Fairly Private: Investigating The Fairness of Visual Privacy Preservation Algorithms. *arXiv* preprint *arXiv*:2301.05012.





Privacy Preservation Reimagined: Top-view Omnidirectional Cameras in AAL





Privacy Preservation Reimagined: Top-view Omnidirectional Cameras in AAL

- Visual privacy preservation algorithms currently focus on lateral-view RGB(-D) camera images.
- Omnidirectional cameras with fisheye lenses provide a better alternative -
 - Less occlusions due to wide field of view, generally cheaper, and less obtrusive.
- A different set of challenges human behaviour understanding (HBU) algorithms don't work due to the heavy distortions from the fisheye lens.
- No datasets exist specifically for Omnidirectional HBU challenges.
- Existing omnidirectional datasets are also mostly either synthetic, or staged.
- Created ODIN a large-scale OmniDirectional INdoor Dataset capturing Activities of Daily Living from multiple synchronised viewpoints.









ODIN - An OmniDirectional INdoor dataset





ODIN - An OmniDirectional INdoor dataset

- Recorded activities of daily living in real indoor environments with varying levels of occlusion.
- 4 locations, 5 environment types, 15 participants, wide range of activities and poses.
- All modalities are synchronised, static cameras are all calibrated.
- First dataset aimed at HBU with top-view omnidirectional images.
- Made to be used for tasks as varied as activity recognition, person tracking and monitoring, scene understanding, biometric monitoring, novel view synthesis, generative modelling, 3D scene reconstruction, and image registration.
- First version of ODIN aimed at omnidirectional 3D human pose estimation.

Modality/characteristic	Amount				
Omnidirectional RGB images	332K				
Lateral-view RGB images	1.464M				
Lateral-view infrared images	1.464M				
Lateral-view depth images	1.453M				
Environment meshes	3				
Egocentric videos	52				
Physiological readings	39				
Accelerometer measurements	39				
Participants	15				
Locations	4				
Types of environments	5				





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ODIN: An OmniDirectional INdoor dataset capturing Activities of Daily Living from multiple synchronized modalities

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Abstract

We introduce ODIN (the OmniDirectional INdoor dataset), the first large-scale multi-modal dataset aimed at spurring research using top-view omnidirectional cameras in challenges related to human behaviour understanding. Recorded in real-life indoor environments with varying levels of occlusion, the dataset contains images of participants performing various activities of daily living. Along with omnidirectional images, additional synchronized modalities of data are provided. These include (1) RGB, infrared, and depth images from multiple RGB-D cameras, (2) egocentric videos, (3) physiological signals and accelerometer readings from a smart bracelet, and (4) 3D scans of the recording environments. To the best of our knowledge, ODIN is also the first dataset to provide camera-frame 3D human pose estimates for omnidirectional images, which are obtained using our novel pipeline. The project is open sourced and available at https://odin-dataset.github.io.

1. Introduction

Challenges relating to the analysis of Activities of Daily Living (ADL) have become essential topics of research in computer vision and active and assisted living [3,7,20]. Examples of these challenges include human pose estimation and activity recognition. For the rest of the paper, these will be referred to as human behaviour understanding (HBU) challenges. Most of the research in these fields is done using lateral-view RGB(-D) images as inputs. However, record-

thy solution to these problems. These cameras are generally unobtrusive, have a larger field of view, and can provide largely unoccluded views of the environments being monitored. However, HBU challenges such as pose estimation become all the more challenging due to the viewpoint and due to the heavy distortions introduced by the lens when compared to wide-angle lenses.

The aim of this work is to introduce a new large-scale omnidirectional dataset which contains numerous synchronized modalities. This includes images and videos from cameras of different types recording participants carrying out various activities of daily living, along with their physiological data. ODIN will support research in areas as varied as human pose estimation, activity recognition, person tracking and monitoring, scene understanding, privacy preservation, biometric monitoring, novel view synthesis, generative modelling, 3D scene reconstruction, and image registration. Through our first release, we aim to promote research on 3D human pose estimation using omnidirectional cameras. Research in this area is scarce, arguably due to the difficulty of the problem and the dearth of datasets For the omnidirectional camera images, the dataset provides associated camera-frame 3D pose estimates. We propose a novel unsupervised pipeline for obtaining these pose estimates in real-life indoor settings while preserving the state of the environment, and also without the use of expensive

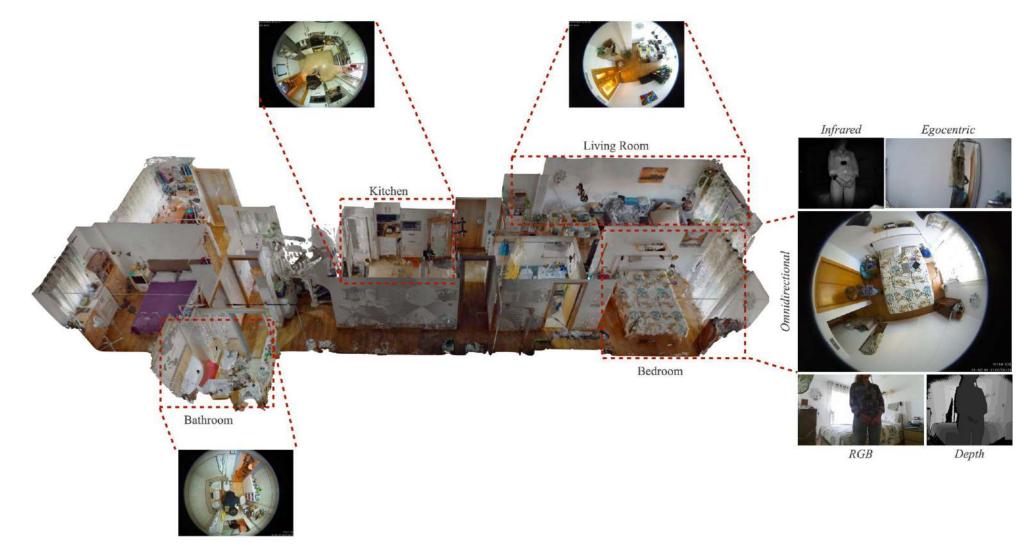
The main contributions of this work are as follows:

 This work introduces a large-scale dataset of omnidirectional images capturing a diverse range of activi-





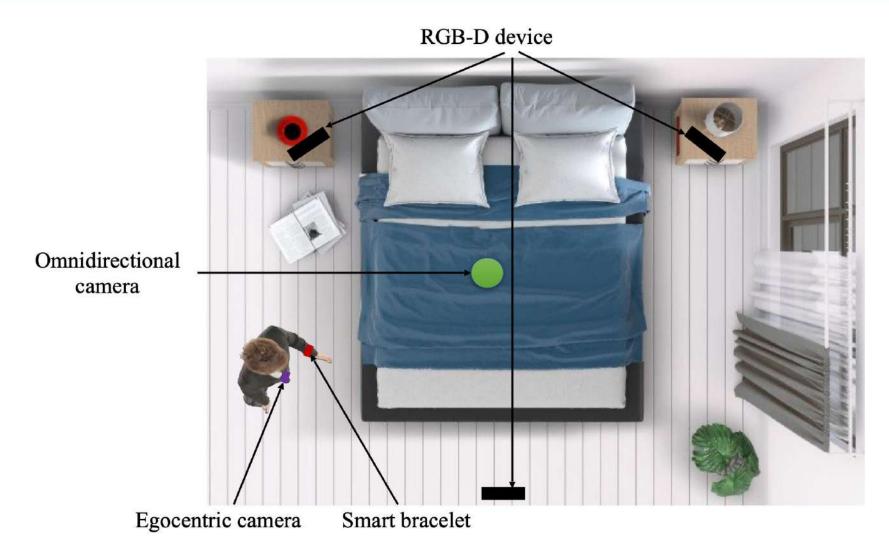
ODIN - environments and modalities







Environment layout







Equipment used



Kinect V2



Xiaomi Mi Action Camera 4K



Empatica E4



D-Link DCS-6010L







A synchronized multi-modal setting













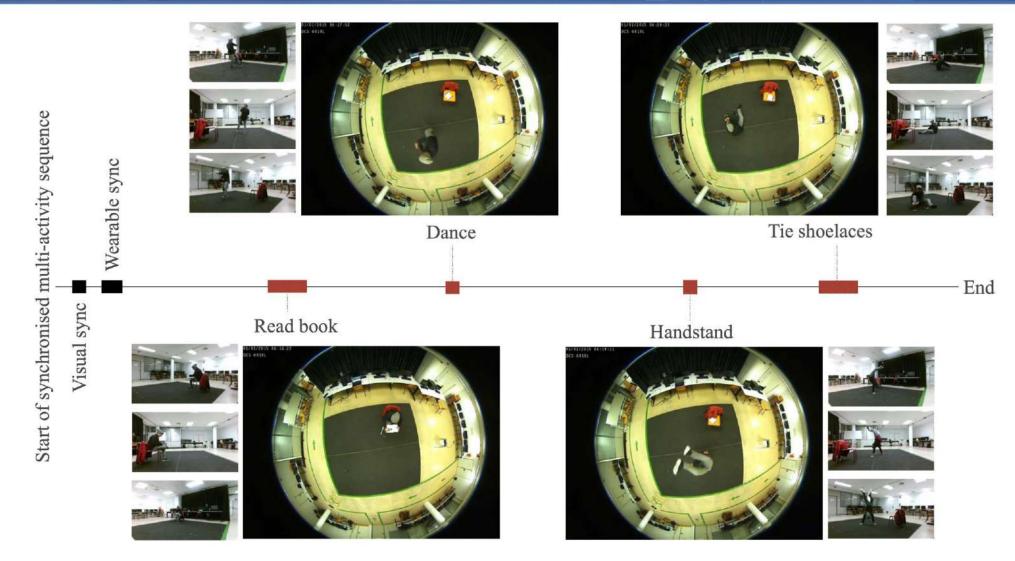
Comparison to related work

Dataset	Omni	Ego	RGB	3D scans	Stereo	IMU	Synced- cam	Phys. signals	Pose	Activity labels	Audio
ODIN	✓	√	✓	✓	✓	(Partial)	✓	√	✓	(x)	×
PIROPO Database	✓	×	×	×	×	×	✓	×	×	\checkmark	×
WEPDTOF	\checkmark	×	×	×	×	×	×	×	×	×	×
Fisheye dataset	✓	×	×	×	×	×	×	×	×	×	×
MPII Human Pose	× ×	×	····√	× ×	×	× ×	×	× ×	·····	× ×	× ×
Human3.6M	×	×	\checkmark	×	×	×	\checkmark	×	✓	×	×
Toyota Smarthome	×	×	\checkmark	×	✓	×	\checkmark	×	\checkmark	✓	×
NTU RGB+D Dataset	×	×	\checkmark	×	\checkmark	×	\checkmark	×	✓	✓	×
ADL Dataset	×	×	\checkmark	×	×	×	×	×	×	\checkmark	×
EPIC KITCHENS	×	\checkmark	×	×	×	×	×	×	×	\checkmark	×
Ego4D	×	\checkmark	\checkmark	\checkmark	✓	\checkmark	✓	×	×	\checkmark	\checkmark





Recording methodology







Pose annotation

- Each omnidirectional image is accompanied by a camera-frame fullbody 3D human pose estimate.
- The pose estimate is obtained by the perspective projection of pose estimates obtained using lateral-view cameras.
 - We calibrate each static cameras against the omnicam to obtain extrinsics.
- A pose annotation pipeline is created for the purpose.







Pose Estimates









Pose annotation pipeline

Lateral-view RGB image

Apply densepose

Detect Person

Obtain 3D poses

Reproject and combine

Omnidirectional 3D human pose estimate

- Obtain IUV maps using Densepose [1]
- Derive segmentation maps
- Detect person in image using a custom metric defined using the body parts seen in the image
- Divide sequence into subsequences with and without person
- Using just subsequences with person, predict camera frame temporal pose using HuMoR [2]
- Use perspective projection to get to top-view omnidirectional pose estimates from each viewpoint.
- Combine 3D poses to obtain a single pose.
- [1] Güler, R. A., Neverova, N., & Kokkinos, I. (2018). Densepose: Dense human pose estimation in the wild. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 7297-7306).
- [2] Rempe, D., Birdal, T., Hertzmann, A., Yang, J., Sridhar, S., & Guibas, L. J. (2021). Humor: 3d human motion model for robust pose estimation. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 11488-11499).





Incorrect Pose







Future Work and Collaborations





Future research plans

- 3D pose estimation benchmarks for ODIN. (end of May 2023)
- Creating improved omnidirectional pose estimation models. (Sep 2023)
- Activity recognition benchmark for ODIN with Kooshan Hashemifard to advance privacy by context. (Oct 2023)
- Secondment in Sweden starting very soon -
 - Investigate privacy preservation from a law perspective.





Thank you!

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