Aria Everyday Activities Dataset

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Abstract

We present Aria Everyday Activities (AEA) Dataset, an egocentric multimodal open dataset recorded using Project Aria glasses. AEA contains 143 daily activity sequences recorded by multiple wearers in five geographically diverse indoor locations. Each of the recording contains multimodal sensor data recorded through the Project Aria glasses. In addition, AEA provides machine perception data including high frequency globally aligned 3D trajectories, scene point cloud, per-frame 3D eye gaze vector and time aligned speech transcription. In this paper, we demonstrate a few exemplar research applications enabled by this dataset, including neural scene reconstruction and prompted segmentation. AEA is an open source dataset that can be downloaded from projectaria.com. We are also providing open-source implementations and examples of how to use the dataset in Project Aria Tools.

1. Introduction

The promise that augmented reality (AR) devices and personal wearable AI devices will be ubiquitous in the future creates the opportunity to develop new technologies that will have profound impacts on people's lives. New AR & AI devices that capture always-on multimodal data from the same egocentric point of view as the wearer provide distinctly new data opportunities and challenges. By leveraging these egocentric devices' continuous contextual data, along with advances in machine learning such as large language models, we will be able to build truely personalized and contextualized AI assistants that can act as an extension to the wearer's mind.

Today's multimodal AI assistants demonstrate intelligent capabilities by leveraging context from texts interleaved with images or short videos, e.g. GPT-4v [18], Gemini [26], Llava [15]., but they only have access to public internet data, plus any prompts the users consciously inputs. We believe that future of AI assistants should be able to access significantly more contextual data about the users, and be able to reason with this data. Firstly, the AI should be able to sufficiently leverage all rich sensor data about its wearer and environment using the sensors and hardware we expect in the future, including spatial audio, motion information and long-duration videos. Secondly, the AI should be able to reason the space-time context in an underlying global coordinate space persistently. Thirdly, the AI should understand the wearer's intent by observing human eye gaze movement or physical interaction using hands.

Empowering the research and applications in these areas will require datasets that are truly representative and contain sufficient contextual data to measure and train novel capabilities. Existing egocentric datasets are primarily captured using traditional video cameras and do not contain all the sensor modalities needed for this research. They usually lack the raw data expected from future AR glasses (such as spatial audio, inertial data), precise 3D location data, time synchronization between modalities and across devices, and the additional personal context to infer the wearer's action or intent.

We introduce the Aria Everyday Activities (AEA) dataset, a 4D dataset with a rich suite of multi-modal sensory information and state-of-the-art machine perception outputs for AI and AR research. The AEA dataset was captured using Project Aria devices [7], a sensor platform with unmatched capabilities for providing always-on egocentric data in an unobtrusive form factor. Aria data includes the following raw sensor data: high resolution RGB video, low resolution global shutter monochrome videos for location tracking, eyetracking videos, two IMU data streams, spacial audio from several microphones, magnetometer data and barometer data. We further provide outputs from our state-of-the-art Machine Perception Services (MPS) [1]. MPS data aims to provide highly accurate and reliable results that can be leveraged as contextual inputs to their models, or used as pseudo ground truth to measure objectives with more strict input constraints.

[1] Machine Perception Services (MPS) documentation page

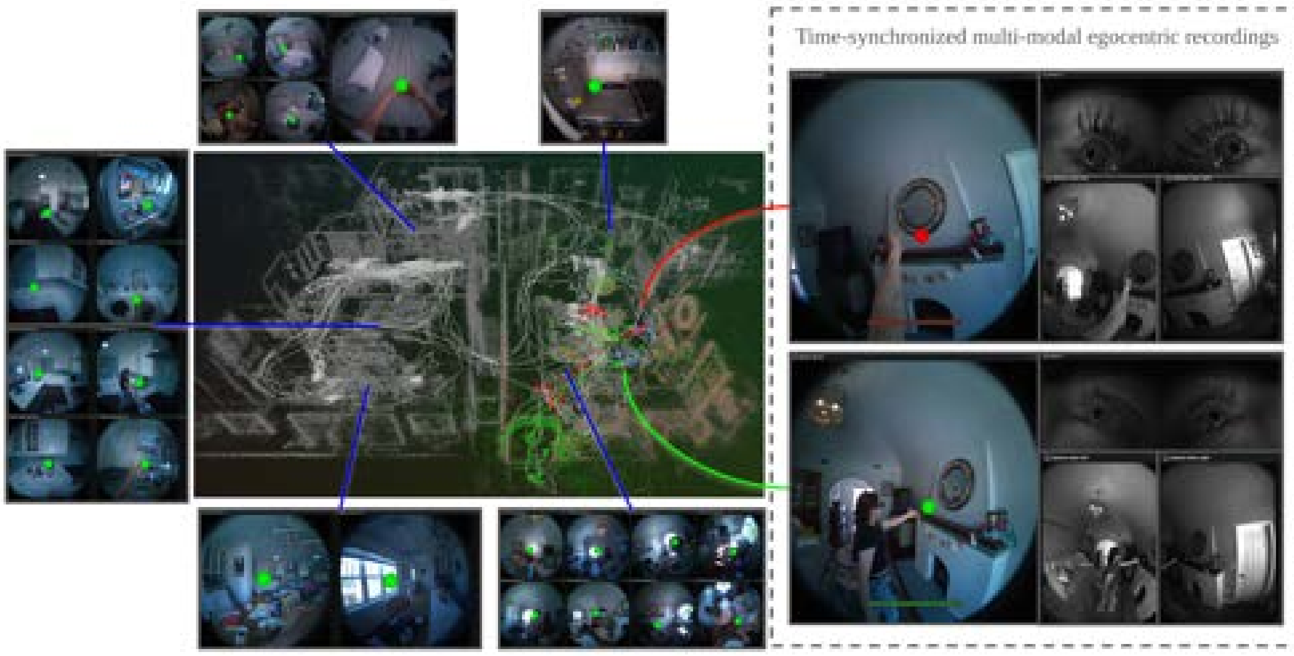


Figure 1. An overview of Aria Everyday Activities (AEA) dataset using some exemplar activities recorded in Location 1. On the right column, we highlight a time-synchronized snapshot of two wearers talking to each other in one activity, with the following information representing each of the viewer in red and green: (1) their high-frequency 6DoF close-loop trajectories, (2) observed point cloud, (3) RGB camera view frustum, (4) monochrome scene cameras, (5) eyetracking cameras, (6) their projected eye gaze on all three camera streams and (7) transcribed speech. On the left side, we also highlight a diverse set of activities (e.g. dining, doing laundry, folding clothes, cooking) with the projected eyetracking (green dot) on the RGB streams. All of the recordings contain close-loop trajectories (white lines) spatially aligned on the environment point cloud (semi-dense points).

AEA is a 4D longitudinal dataset with all daily activity recordings aligned spatial-temporally. AEA contains 143 activities recorded by multiple wearers in 5 locations that are representative for multi-person activities in a day. In additional to an on-device high frequency trajectory that provides 6DoF poses, AEA contains globally aligned 3D context for all observations in the same location. In each location, all the recordings from different wearers contain the aligned trajectories and a global point cloud in the same 3D coordinate system. To indicate each wearer's intention, we provide the processed eye gazed calculated from the eyetracking camera streams. We further provide the time-aligned transcription of speeches in the recordings. For multi-person activities, all the recordings are time-synchronized accurately with external timecode, which ensures all the different observations are synchronized accurately not only in the space but also in the time domain.

The AEA dataset is an updated version of the Everyday Activities section of the Aria Pilot dataset (APD) [17], the first publicly released Aria dataset. This dataset has served as the first stop to attract researchers experimenting with Project Aria data in various research areas. Since APD's launch, Project Aria has been used in several new public datasets, including the Aria Digital Twin dataset [19], the Aria Synthetic Environments dataset, and the Ego-Exo4D dataset [10]. Along these open data releases, Project Aria has improved the MPS and open-source tooling it provides [7].

In the AEA dataset, we provide three major updates to the original pilot dataset. First, we updated the data formats to be consistent with our new open-source tooling, allowing users to load and query data using a unified set of tooling across all Aria public datasets. Secondly, we reprocessed the raw Aria recordings with most recent Machine Perception Services, providing the following improvements: (1) more precise 6DoF pose information, (2) newly generated semi-dense point cloud with 2D observations, (3) more precise calibrated eyegaze with 3D directional vector, and (4) per-frame sensor extrinsic and intrinsic calibrations. Thirdly, we augmented our open-source tooling with easier data loading capabilities in C++ and Python, and created tools for running hands-on examples discussed in this paper. Among the existing Project Aria datasets, AEA will continue to serve as a unique dataset that enables researchers to study the egocentric everyday activities with all the recordings and machine perception context aligned in the same space and time coordinate frames.

To further illustrate the capabilities of the AEA dataset in research, we have provided exemplar applications in neural reconstruction and prompted segmentation. In neural scene reconstruction, we demonstrate how to leverage the closed loop trajectories and global point cloud to reconstruct the observed scenes from either a single recording, or multi-recordings jointly using recent advances in Gaussian Splatting [11]. Finally, we've provided two prompted segmentation examples using Efficient-SAM [29], a distilled variant of the powerful foundational model SAM [12], and grounding-DINO [16] to demonstrate how we can easily prompt the foundational model with wearer's input using eye gaze and speech. We hope these exemplar applications can inspire researchers to explore more powerful AI with this rich context.

In summary, we present the AEA dataset, a multi-person everyday activities dataset recorded using Project Aria glasses, with multi-modal sensory data and 4D space-time aligned machine perception information. In this technical report, we will first discuss the related work in Sec.2. We will describe the major aspects of this dataset in Sec.3 and provide open source tools in Sec.4. Sec.5 provides a few example research applications using this dataset.

2. Related Work

In this section, we review prior work with a particular focus on datasets that have served the egocentric AI and 3D multimodal research community.

Egocentric datasets: The first-person vision (FPV) and egocentric datasets [1, 6, 9, 13] have served as an important role to drive research development in egocentric video understanding and AI. The two seminal datasets EpicKitchen [5, 6] and Ego4D [9] set up a number of egocentric understanding benchmarks paired with extensive egocentric videos and annotations. These datasets were primarily captured by video recording devices mounted on wearer's head, e.g. a GoPro head-mounted camera rig. They lack other important sensor modalities required to more accurately infer 3D information or wearer intention. Due to the nature of rapid head-motion in egocentric videos, precisely and reliably estimating the 3D information in all the videos is still a very challenging research problem. A small subset of Ego4D videos rely on relocalization using a pre-scanned 3D environment. EpicFields [27] recovered part of the 3D environments and trajectories using COLMAP [22] and neural fields. In the AEA dataset, we provide 6DoF 1KHz trajectories which approximate the continuous 6DoF trajectory of the egocentric observer for every single recording generated by the foundational capabilities of the Project Aria device using the state-of-the-art visual-inertial odometry (VIO) and simultaneous location and mapping (SLAM) systems. AEA also contains calibrated eye gaze information for every recording. Existing dataset GTEA [14], EGTea [13], and a small subset of Ego4D dataset contain eye-gaze information, but they do not contain other 3D information, which can create hurdles when contextualizing the wearers' intention in a 3D environment.

Project Aria datasets: AEA is an updated dataset based on the Everyday Activities sequences in the Aria Pilot dataset [17]. Since the Aria Pilot dataset's release, more datasets have been recorded using Project Aria devices that feature different capabilities and tasks. Aria Digital Twin (ADT) [19] contains real-world activities captured by Aria wearers in two environments that have been fully digitized with precise object and wearer poses. For all the Aria recordings, ADT contains the same raw sensor information, with additional ground truth rendered from the a motion capture system (MCS) aligned with the digitized scene. There are also some visual artifacts in the dataset to enable the MCS. Creating such a dataset requires extensive efforts and resources which can be difficult to scale up.

In contrast, AEA was recorded in five diverse fully consented environments with no other requirements in the scene. We record multiple daily activities and acquired derived machine perception data using Project Aria's Machine Perception Services (MPS). AEA serves as example for Project Aria recordings that can be easily scaled up for research that requires extensive egocentric data capture.

The recent effort of Ego-Exo4D dataset [10] features the largest multi-modal egocentric datasets using Project Aria as the egocentric recording device. It contains both egocentric and exocentric devices accumulated in 1400 hours. The dataset also uses MPS to generate per-recording machine perception data. The main differences between AEA and Ego-Exo4d are in the type of activities and environments being considered. Ego-Exo4d focuses on procedural activities, while AEA focuses on longitudinal daily activities in a whole day in home locations. In AEA, we provide multi-person synchronized egocentric recordings, and multi-trajectory recordings aligned in one home, while Ego-Exo4d provided synchronized captures between the egocentric videos with respect to the exocentric captures in a constrained cubic space observable from all cameras. We believe AEA can serve as an important pilot egocentric dataset for AI research that requires natural 3D environments and long-range spatial-temporal aligned videos.

Other 3D multimodal datasets: Recently, there have been a few other datasets introduced which were recorded using other head mounted devices in a more cumbersome form factor. Assembly101 [23] uses Meta Oculus Quest devices and operate a series of assembly activities under a multi-view desktop environment. HoloAssist [28] features

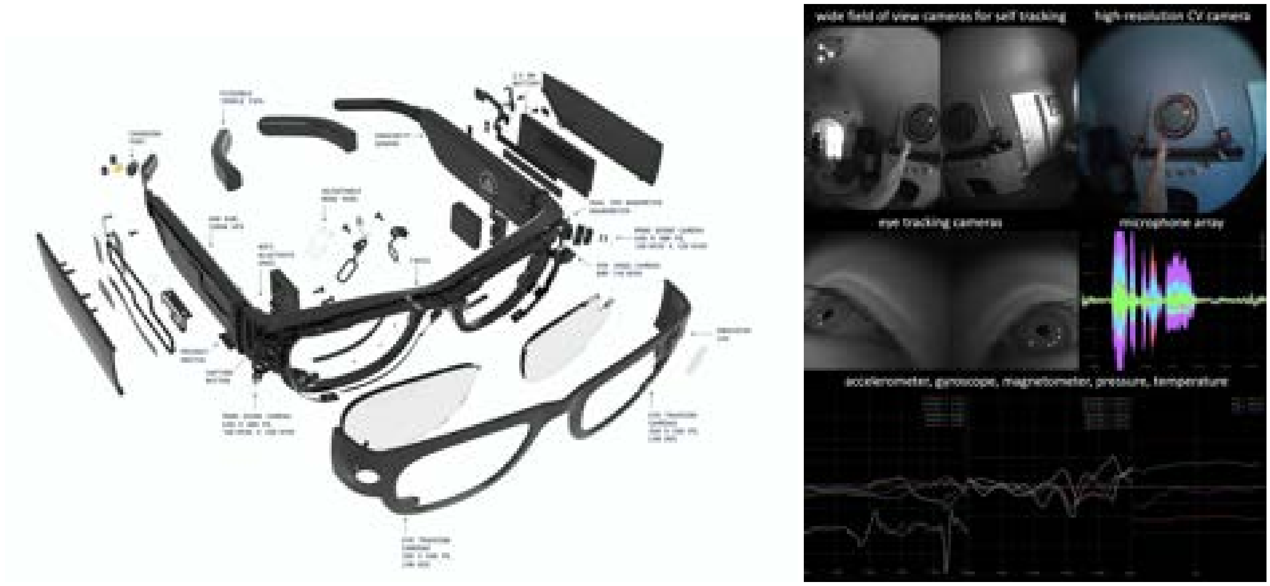


Figure 2. An overview of components on Project Aria device, with exemplar senor configuration of each. In this dataset, we use Profile9 which include all the sensors of the device except the WiFi, Bluetooth & GNSS. We visualize a snapshot of all the sensors in one of the recordings on the right.

Location	Recording Scripts	Wearers	Recordings	Image Frames	RGB Frames	Total Duration (hours)
Location 1	Scripts 1-5	1-2 Wearers	29	230,487	115,235	1.6
Location 2	Scripts 1-5	1-2 Wearers	43	339,650	169,824	2.3
Location 3	Scripts 1-5	1-2 Wearers	38	259,027	129,514	1.7
Location 4	Scripts 1-5	1-2 Wearers	19	94,029	47,015	0.6
Location 5	Scripts 4-5	1 Wearer	14	168,428	84,214	1.1
In total	Scripts 1-5	1-2 Wearers	143	1,091,621	545,802	7.3

Table 1. Data statistics for the recordings at each location. Refer to Appendix C to more details of the recording scripts. The total number of image frames account for a combination of all RGB image frames and monochrome scene camera frames.

several two-human collaborative tasks using the Hololens headset. Compared to these datasets, AEA features more natural human activities in indoor locations, with the benefits of non-obtrusive Project Aria form-factor.

The study of multimodal research also extensively uses Autonomous driving datasets [3,8,24], which provides very different scenarios and sensor modalities. The future of multimodal learning in personal AI will require datasets collected using similar device form-factors to future AR glasses and datasets that closely resemble the human activities in one's daily life. We believe AEA will serve as an exemplar dataset to drive research in this domain.

3. Dataset Description

The Aria Everyday Activity (AEA) dataset is an updated version of Everyday Activity sequences within the Aria Pilot Dataset (APD). APD was the first publicly released dataset collected using Project Aria devices. It introduces a 4D longitudinal dataset with all day activity recordings captured by always-on form factor glasses with spatial-temporally aligned metadata. For the new AEA dataset, we updated all the machine perception data using the most recent Machine Perception Services (MPS) for all recordings, to provide the best 3D information possible. We describe the details of the AEA dataset below.

Dataset statistics: AEA contains 143 recordings of everyday activities collected by multiple wearers in five indoor locations. In total, it is composed of over 1 million frames with 7.3 accumulated recording hours. There are over 2 million image frames accounting for RGB color images and monochrome scene images. Tab. 1 shows the data statistics for the number of wearers, recordings and frame numbers in each location.

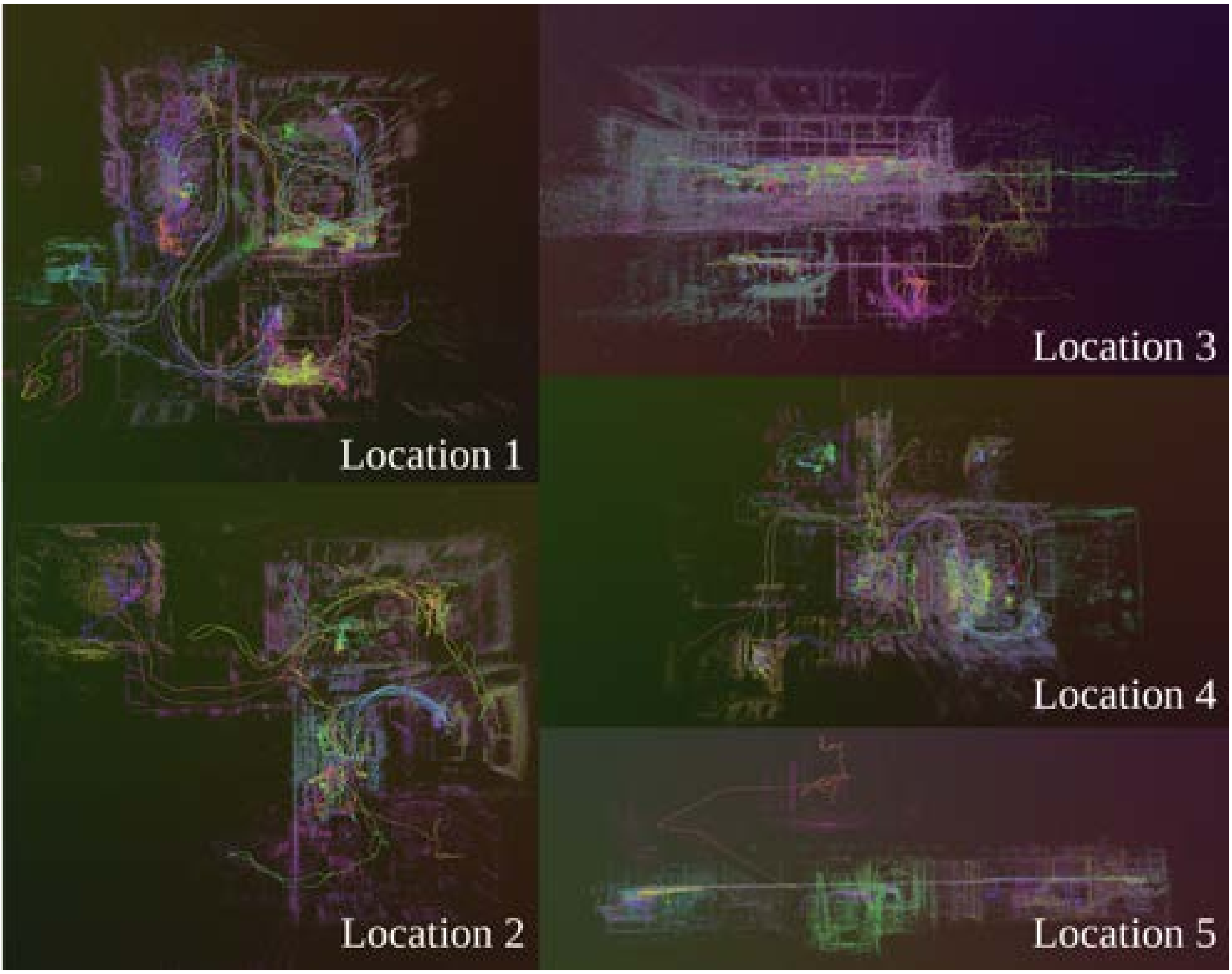


Figure 3. A visualization of the shared 3D global closed-loop trajectories and the semi-dense point clouds for multi-recording activities on every 5 location. Each color indicates the high frequency trajectory of one sequence recorded in this location. In each location, the point clouds are aggregated from all recordings. Location 3 and 5 are shown sideways to highlight the multi-floor scenarios.

Dataset collection process: We created guidance scripts for wearers to represent all day longitudinal activities that can be observed with always-on sensing for one to two Project Aria device wearers. Each script contained multiple scenarios that told a story about people going through their day. The scripts only provided general guidance for an improvised scenario. Wearers followed the provided prompts and went with what felt most natural to them in each of the recordings. The scripts can be used as an open-vocabulary description for the egocentric activities. Some of the scripts scenarios are: cooking, daily cleaning, exercising, dining, reading, playing games and spending time with friends. We provide details about how the scripts correspond to specific tasks in Appendix C.

Aria raw sensor data: We used the *recording Profile 9* provided by Project Aria data collection configurations, with 20 fps RGB camera at 1408×1408 resolution, 10 fps monochrome scene cameras at 640×480 resolution, 10 fps eye tracking camera at 320×240 resolution, and all other sensors configured at their default settings. Refer to Appendix A for more details of the raw senor description.

Machine perception data: This is a major feature update in AEA dataset compared to recordings in Aria Pilot Dataset. AEA uses the current Machine Perception Services (MPS) provided to Project Aria academic partners. The data format has been updated to be consistent with the new official Project Aria data format convention used in Project Aria Tools, the new opens source tooling and documentation repository. There are two major updates to the MPS data compared to the Aria Pilot dataset,

- **3D location**: We've provided 6DoF trajectories aligned with visible global point cloud for each recording, which shares the same coordinate system with all other recordings in the same location. The global point cloud is a reconstruction using tracked feature points of the static portion of the environment. We call the 3D point cloud as *semi-dense points* and the 2D tracked points as *semi-dense observations* in MPS. We only provided 1Khz trajectory for each recording in the initial Aria Pilot Dataset. In this update, we have added semi-dense points aligned with each trajectory in the global coordinate space, which we call *close-loop trajectory*. Fig. 3 shows the visualization of all spatial aligned recordings in each location. We've manually inspected the trajectories and point cloud for all recordings in the global aligned coordinate to ensure they are correct.
- **Eye gaze with 3D directional vector** : AEA provides calculated 3D eye gaze as a per-frame 3D ray anchored on the Central Pupil Frame. This provides more information in the 3D environment compared to the initial release of 2D reprojected eyegaze point in RGB camera. We've also provided code examples in Project Aria Tools to acquire the 2D eye gaze using device calibration.

We've also provided on-device odometry, which we call *open-loop trajectory* and online device calibration. Both of these features were not available when we released the pilot datasets. For more details about the machine perception data and MPS, please refer to Appendix B.

Time synchronization: AEA includes several multiple-person activities, such as two people having a conversation. In multi-person scenarios, we captured the recordings with synchronized timestamps. Multiple Project Aria devices that operate in proximity to each other ($< 100m$) can leverage SMPTE LTC timecode to receive a synchronized time clock with sub-millisecond accuracy. In the VRS file, we've provided synchronized timecode timestamps shared across multi-device captures in addition to the capture time of each device. Different recordings captured at the same time can be associated using the device timecode. We also provide a toolkit to visualize the synchronized recordings, which we will illustrate in Sec. 4.

Speech2text transcription: We've used the same text transcription generated by Automatic Speech Recognition (ASR) released in APD. All characters in text are aligned with the device timestamp, and each output is also associated with a confidence rating. The ASR annotation used

Figure 4. We manually blurred all the human faces in both RGB color video (right) and two monochrome scene camera videos (cropped in the left two images).

a proprietary service that is not part of Project Aria MPS. Similar results can be acquired via open-source ASR solutions, such as [4, 21]. We hope the released speech transcription can accelerate the research and applications that require time aligned text input.

Privacy commitments: We strictly follow the Meta's Responsible Innovation Principles for all data collection and processing. All of the recordings were captured in fully consented indoor environments with no personal identified information. To ensure the highest quality of anonymization, we manually annotated and blurred all the faces and licenses on all images in RGB and monochrome scene camera streams. We carefully verified the annotation results with multiple rounds of quality analysis. Recordings flagged with frames that did not pass quality check were completely excluded from the dataset. Fig 4 shows an example of the anonymization for RGB and monochrome sensor streams.

4. Dataset Tools

To support the release of this dataset we updated Project Aria Tools, which provides the open source data utilities for working with Aria data. This update provides data providers to consume the multimodal sensory data and their paired machine perception data from multiple devices. All data modalities and metadata can be retrieved by their device *timestamp*. Manipulating single or multiple-person activities can be done with ease. Project Aria Tools also provides convenient APIs to use the device & camera calibration to manipulate the 6DoF pose transformation as well as 2D/3D points projection and reprojection between the various sensors.

Project Aria Tools provides a visualization tool to support users quickly exploring each sequence or multi-person scenario with temporal scrubbing. Fig. 5 shows an example

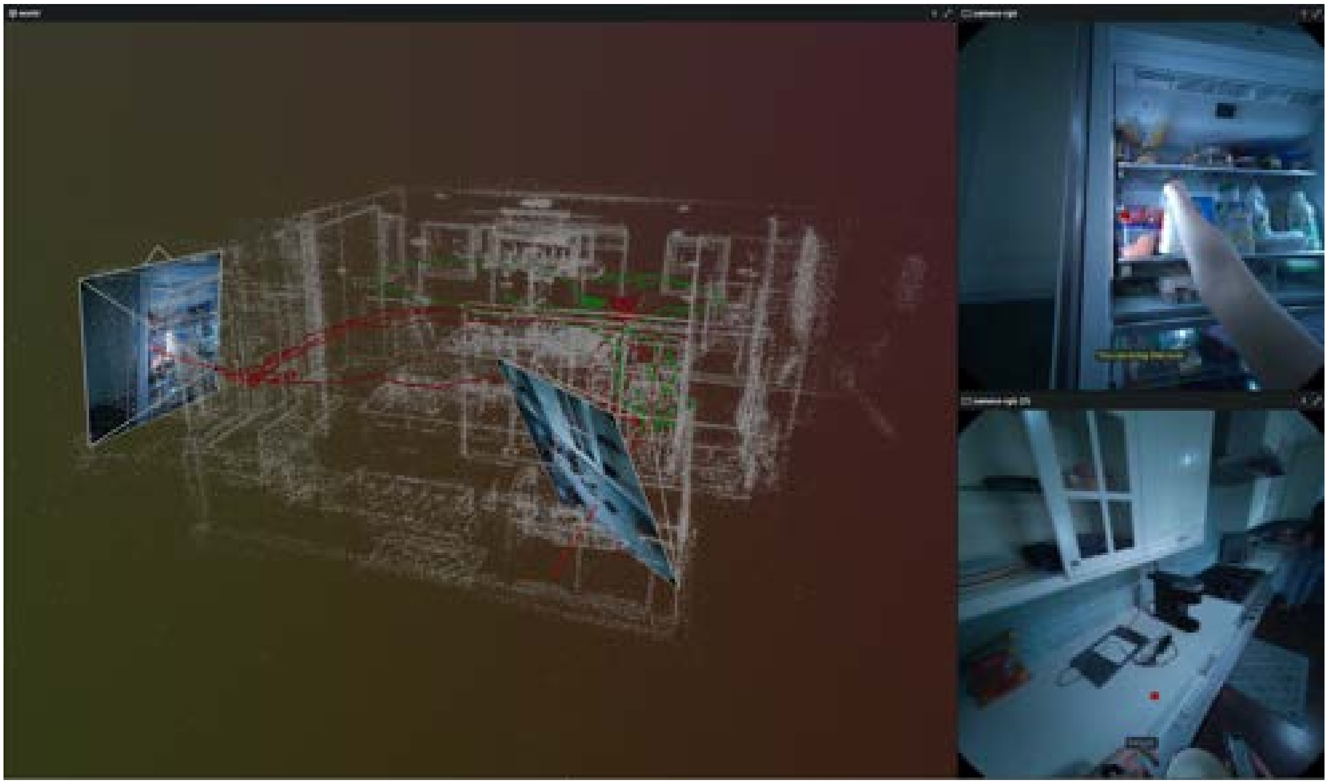


Figure 5. A snapshot of AEA dataset viewer (multiple-person activity) showing the synchronized rectified RGB streams with their devices trajectories (dark red and green of each), eye gaze vector direction (a red vector from each device frustum), the projected eye gaze on RGB image (red dot in each image), the aggregated 3D semi-dense point cloud for each recording (white) and the transcribed speech sentences (overlaid on each RGB image). We provide this viewer in project aria tools.

of two time synchronized recordings with their 3D trajectory, environment as global point cloud and eye gaze vectors visualization all in one shared coordinate. We also display the synchronized text from speech as an example of other temporal data, which is queried according to the device time. This could be easily extended to display additional user metadata or more recordings for development and debugging.

5. Applications

We provide two main research applications of the AEA dataset in this section, 3D neural scene reconstruction, and prompted segmentation. These exemplar applications demonstrate strong use cases for using AEA multimodal egocentric observation and machine perception data. We hope they can give a glimpse of research using this dataset.

5.1. 3D Neural Scene Reconstruction

Reconstructing scenes for observable areas is one important problem to create immersive photo-realistic virtual memories in AR/VR applications. Existing neural reconstruction methods usually require a two-step approach. Given one video sequence, they acquire the 6DoF camera trajectory from a structure-from-motion (SfM) tool, e.g. COLMAP [22], and then run neural reconstructions on the posed images. This can be challenging for egocentric activities, where the recordings are not carefully taken and curated for the purpose of running SfM. Rapid head motion or less observable areas can easily lead to failure of SfM or similar localization algorithms, and fail further reconstructions. For multiple long recordings in the same environment, it can also be challenging to jointly localize all the observations in a shared coordinate system.

It is worth noting that the AEA dataset is activity-centric. Every recording contains various egocentric motions and may also observe moving humans in multi-person activities. All of the trajectories are free-view motions that are drastically different from traditional datasets made for object or static scene oriented reconstruction purposes. Despite these challenges, we demonstrate that we can successfully reconstruct scenes that are persistent across one or multiple recordings. We hope this can inspire future research to improve the reconstruction quality when there are dynamic motions, or improve activity & scene understanding with fully immersive environments.

In this section, we demonstrate running neural reconstruction and address the aforementioned challenges using 3D machine perception data from the AEA dataset, in particular the closed-loop trajectory and semi-dense point cloud. We use Gaussian-splatting [11] as the primary baseline and provide a full evaluation.

5.1.1 Gaussian splatting

Implementation: We followed the official implementation of Gaussian Splatting, except for a few minor changes to support multi-sequence reconstruction. Since we reconstructed long trajectories which could not be loaded directly into memory, we used batch processing to randomly seek a batch of frames at runtime. We used Project Aria Tools to rectify all the RGB images that fit in the requirements of the default pinhole rasterizer. We initialized the point cloud using the AEA semi-dense points, and acquired per-frame poses using the pose with the nearest timestamp from the high-frequency closed-loop trajectory. For multi-recording reconstructions, we concatenate all the frames, and point clouds together. We ran 30K iterations for single-recording reconstruction and 100K iterations for multi-sequence reconstructions. All reconstructions shared the same hyper-parameters and strategy for pruning and densification. On a single A100 80GB GPU, reconstructing a single recording took about 3 hours, and 10 hours for multiple recordings in one shared location.

Single Recording Results: This method successfully converged on each recording individually, despite some recordings having high dynamic motion or minimal head motions. Fig. 6 shows a few rendering examples with the nearest view in the 3D space. In the results, we saw good quality reconstruction for all well-observed static areas. The blurry areas rendered from Gaussians indicate the dynamic or unobserved areas in the original observation.

Multi-recording Results: We further ran Gaussian Splatting on all recordings aggregated in each location. The number of recordings and frames can be found in Tab.1. For example, location 2 contained the longest recordings accumulated with total length of 2.3h, close to 170K RGB frames, and 5M initial points aggregated from the semi-dense point clouds. After 100K iteration of reconstruction, location 2 converged to about 627K Gaussian points. Fig. 7 illustrates a few rendered views. Given the abundance of observations in one location, we could reconstruct well-observed living areas and remove the image areas with dynamic motions as outliers in each.

Quantitative Evaluations: Tab. 2 shows the quantitative reconstruction quality evaluated for each location, in single recording (SR) and multi-recording (MR) settings. We reported the PSNR number averaged for all the held-out test frames. The test-frames were the last-frame out of every 5 consecutive frames.

Location	PSNR (SR)	PSNR (MR)
Location 1	25.79	22.85
Location 2	25.19	21.93
Location 3	24.85	22.06
Location 4	23.70	21.83
Location 5	26.27	24.18
Locations all	25.12	22.35

Table 2. Quantitative evaluation of Gaussian-splatting on the held-out testing frames (The last frame out of every 5 frames). We report the PSNR averaged for all frames in single recording (SR) or multiple recordings (MR) scenarios.

5.1.2 3D Reconstruction using NeRFstudio

NeRFstudio [25] provides an Aria customized integration for processing Aria raw data using the trajectories and global point cloud provided by MPS. The NeRF baselines, e.g. NeRFacto use the Aria closed-loop trajectories and raw RGB images as input. Its Gaussian-splatting baseline (aka Splatfacto) also uses semi-dense point cloud data to initialize the 3D Gaussians and rectify the RGB images as we demonstrated. To achieve the best results on AEA, some adjustments in the current implementations were needed to accommodate the length of recordings. We will continue to support open-source implementation of scene reconstruction using Project Aria data, and plan to reconstruct AEA dataset with baselines in NeRFstudio in the future work.

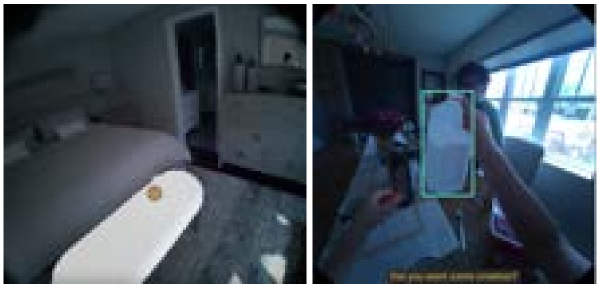
5.2. Prompted Segmentation

The ability to recognize and segment object instance in the 3D environment is one of the fundamental components in contextual AI applications. The recent progress in 2D foundational models show a promising path to enable zero-shot AI capabilities with good generalization, e.g. CLIP [20], DINO [2], SAM [12]. In this section, we use segmenting anything model (SAM) as an example to show multiple sensor modalities can be helpful for AI research. We use the EfficientSAM [29], which is a variant of SAM, as it provides a good balance between accuracy and real-time performance when running on every RGB frame.

In this example we show two applications connecting EfficientSAM with two different prompts from the machine perception data. First, we show how to segment objects using the eye gaze as the prompt of wearer's intention. Then, we further connect EfficientSAM with GroundingDino [16] to demonstrate speech grounded segmentation. Both ap-

Figure 6. Novel rendering views of the Gaussian-splatting reconstruction (top) and their corresponding nearest neighbor views (bottom) using observations **from a single recording**.

Figure 7. Novel rendering views of the Gaussian-splatting reconstruction using observations **from all recordings in the shared location**. The corresponding nearest neighbour views are shown on the second row.



(a) Eye gaze prompt (b) Speech prompt

Figure 8. We demonstrate multimodal prompted segmentation to highlight what the wearer is looking at or talking about. The eye gaze projection is used as point prompt to EfficientSAM [29] in (a) and speech is used to prompt GroundingDino [16] to detect the object and further segment them out using EfficientSAM in (b).

plications are provided as implementation examples in the Project Aria Tools.

Eye-gazed prompted segmentation: Fig.8a shows the visualization of segmentation using projected eye-gaze in one RGB image as a prompt. Given the eye gaze directional vector and a virtual depth along this vector, we projected it into 2D RGB image stream using the device calibration, and then used the 2D reprojected eye gaze as the location prompt to produce a segmentation mask with EfficientSAM. In this example, we set the virtual depth at 1.0 meter. Future work can improve prompt accuracy by incorporating a more accurate eye gaze depth estimator.

Speech grounded segmentation: Fig.8b shows a visual grounding of an object mentioned in the speech. Given a time-aligned speech sentence, we first used GroundingDino [16] align the text with the image and detect the objects in the sentence. If an object existed, the corresponding bounding box was used as the box prompt and EfficientSAM [29] produced a segmentation mask within it.

6. Conclusion

We introduce the Aria Everyday Activity (AEA) Dataset for the research community to explore multimodal AI research with real world personal longitudinal activities that have spatial-temporal alignment context. This dataset is an updated version of the Everyday Activity sequences in the Aria Pilot Dataset. We updated the previous release using the most recent Machine Perception Services provided by Project Aria team and demonstrate a few research applications enabled by the machine perception data. We have also updated the open source Project Aria Tools to be compatible with this dataset and have provided a few research application examples. We believe AEA can serve as useful resources to enable researchers exploring always-on multimodal contextual AI research.

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A. Project Aria Raw Sensor Data Description

Project Aria devices integrate a variety of sensors that record egocentric multimodal data that can be configured optionally at run-time by users. For a more comprehensive description of Project Aria devices, readers can refer to the device description in Project Aria white paper [7]).

To fully empower multi-modal research in everyday scenarios, we chose a recording configuration that provided a rich suite of sensors appropriate for an indoor setting. The sensors used to generate raw data were:

RGB Camera: This is a rolling shuttle camera with 110° horizontal field of view (HFoV). We captured the RGB stream at 20 fps with a resolution of 1408x1408 pixels.

Monochrome Scene / SLAM Cameras: These cameras are global-shutter monochrome cameras with 150° HFoV, placed on left and right side of the glasses. These two cameras are primarily useful for visual SLAM and can also be helpful for hand tracking. We recorded each monochrome video stream at 10 fps with a resolution of 640x480 pixels.

Eye Tracking Cameras: There are two monochrome inward facing cameras with IR illumination used for eye tracking purposes. They recorded at 10 fps with a resolution of 320x240 pixels and 80° diagonal field of view (DFoV).

IMUs: There are two inertial measurements units (IMU) on each side of the glasses. The left IMU runs at 800 Hz with a saturation limit of 4g (accelerometer) and $500°/s$ (gyroscope). The right IMU samples at 1000 Hz with a saturation limit of 8g (accelerator) and $1000°/s$ (gyroscope).

Microphone: There are 7 microphones in the glasses, five face the front plus one on each side. We captured spatial audio with 7 channels using a sample rate of 48kHz.

Other sensors: A magnetometer measured the ambient magnetic field with a resolution of $0.1T$ at a sample rate of 10 Hz. A barometer sensor captured local air pressure and temperature at a resolution of $0.66Pa$ and $0.005C$, respectively at a sample rate of 50 Hz. We did not turn on GPS or WiFi sensors during any of the recordings.

B. Machine Perception Services (MPS)

In addition to raw sensor data, we've provided a range of machine perception capabilities that further empower downstream applications that require reliable 3D and eye-gaze information derived from the sensors. We acquire the location and eye gaze information using the Machine Perception Services (MPS) provided by Project Aria, which has superior accuracy and robustness compared existing off-the-shelf open source solutions. For speech transcription, we used an in-house speech recognition model. Please refer to [7] for more details about Machine Perception Services.

Open-loop trajectory: For each of the recording, we provided a high frequency (1 kHz) 6DoF trajectory from the real-time odometry estimation. This trajectory is suitable to be used to mimic any real-time applications that require on-device 6DoF pose information.

Close-loop trajectory: This is also a high frequency (1 kHz) 6 DoF trajectory, but acquired via post-processing. Unlike open-loop trajectory, this trajectory shares the same reference frame from all other sequences recorded at the same location. This ensures we can align all the trajectories from different recordings by multiple wearers doing multiple activities in the same location.

Semi-dense Points: In addition to the close-loop trajectory, we've provided semi-dense tracks and point cloud using the same global frame of reference, which is a partial reconstruction of the static portion of the environment. Fig. 3 shows the visualized point cloud together with closed-loop trajectory from all different activities performed by one user in the same location during a day.

Eye-gaze tracking: We've provided calculated 3D eye gaze from the Project Aria device eye tracking cameras.

This is represented as a per-frame 3D ray anchored to the central pupil frame. Using device calibration, we can also project the ray to each 2D camera and get an eye gaze location using an estimated depth along each ray. The gaze information is an important indicator of wearer's attention, which can be helpful for a variety of contextual AI applications.

C. Activity Scripts in Data Collection

We provided five main recordings scripts as guidance in the data collection. In each location, the wearers will perform guided activities follow all the high-level scripts. Each script contained multiple scenarios that told a story about people going through their day.

- Script 1: A lazy morning before the party. – Single wearer
- Script 2: Catch up and have some fun. – Two wearers
- Script 3: What do you want for dinner? – Two wearers
- Script 4: Easy like Sunday morning. – Single wearer
- Script 5: Get home then get going. – Single wearer

Each script is connected by multiple sequential activities in a day. We provide the guidance activity name paired with each script ID and sequence ID in Tab.3.

We provide downloading scripts for readers to download the data in one location, which contain all available sequences in all scripts. It is worth noting that not all activities are available to be downloaded for each of the script in every location. We have done a rigorous quality analysis on the collected recordings, which have filtered out certain recordings that do not pass our quality analysis.

We further categorize the activities into a few common taxonomies and provide the list to identify where scenarios are used in scripts. The Wearer numbers indicate how many wearers were in a sequence. We provide the details of the activity to scripts mapping in Tab.4.

Script ID	Sequence ID	Open World Activities
1	1	Health activity
1	2	Watch TV
1	3	Clean the place
1	4	Room Decoration
1	5	Video game break
1	6	Food and accomodations
1	7	Read and wait
2	1	Friends arrives at home
2	2	The home tour
2	3	Caffeination
2	4	Grab cream, sugar and snacks
2	5	Play a board game
2	6	Clean a spill
2	7	Share some vides
2	8	Time to go
3	1	Texting and Reading
3	2	Talk about the day
3	3	Cooking
3	4	Set the table and eat
3	5	Clean up
4	1	Waking up
4	2	Perk up with coffee
4	3	Morning exercise
4	4	Prepare breakfast
4	5	Eating
4	6	Clean up
4	7	Relaxing
5	1	Get home
5	2	Wash the clothes
5	3	Straighten up
5	4	Dry your clothes
5	5	Catch up on what happened
5	6	Get and fold the laundry
5	7	Check the food provisions

Table 3. The activities mapped to each sequence in the recording scripts.

Task	Script ID	Number of Wearers
Making coffee	Script 2: Caffeination	2
Making coffee	Script 4: Perk up	1
Prepare snacks	Script 1: Set out food and drink	1
Prepare snacks	Script 2: Grab the cream, sugar, and some snacks	2
Cooking	Script 3: Cooking	2
Cooking	Script 4: Breaking the Fast	1
Cooking	Script 5: Check the provisions	1
Clean the place	Script 1: Clean the place	1
Clean the place	Script 2: Clean up spilled coffee	2
Clean the place	Script 2: Time to go	2
Clean the place	Script 3: Clean up	2
Clean the place	Script 4: Cleaning up	1
Dining	Script 3: Set the table	2
Dining	Script 4: Eating	1
Organization and laundry	Script 1: Put up decorations	1
Organization and laundry	Script 5: Get home	1
Organization and laundry	Script 5: Wash clothes	1
Organization and laundry	Script 5: Straighten up	1
Organization and laundry	Script 5: Dry clothes	1
Organization and laundry	Script 5: Get and fold laundry	1
Reading, games and exercise	Script 1: Get the blood pumping	1
Reading, games and exercise	Script 1: Watch a TV Show	1
Reading, games and exercise	Script 1: Video game break	1
Reading, games and exercise	Script 1: Read and wait	1
Reading, games and exercise	Script 4: Waking up	1
Reading, games and exercise	Script 4: Exercise	1
Reading, games and exercise	Script 4: Play console video game	1
Reading, games and exercise	Script 5: Catch up on email and social media	1
Touring the room	Script 2: Tour of the house	2
Multi-person indoor activities	Script 2: Guest arrives	2
Multi-person indoor activities	Script 2: play a board game	2
Multi-person indoor activities	Script 2: Share videos	2
Multi-person indoor activities	Script 3: Arriving home	2
Activities with indoor outdoor transitions	Script 2: Guest arrives	2
Activities with indoor outdoor transitions	Script 3: Arriving home	2
Activities with indoor outdoor transitions	Script 5: Get home	1

Table 4. The details of all activities mapped to each recording script.