SANPO A Scene Understanding, Accessibility, Navigation, Pathfinding, Obstacle Avoidance Dataset

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ABSTRACT

We introduce SANPO⁴, a large-scale egocentric video dataset focused on dense prediction in outdoor environments. It contains stereo video sessions collected across diverse outdoor environments, as well as rendered synthetic video sessions ⁵ All sessions have (dense) depth and odometry labels. All synthetic sessions and a subset of real sessions have *temporally consistent* dense panoptic segmentation labels. To our knowledge this is the first human egocentric video dataset with both large scale dense panoptic segmentation and depth annotations.

In addition to the dataset we also provide zero-shot baselines and SANPO benchmarks for future research. We hope that the challenging nature of SANPO will help advance the state-of-the-art in video segmentation, depth estimation, multi-task visual modeling, and synthetic-to-real domain adaptation, while enabling human navigation systems.

1 Introduction

Egocentric scene understanding is an important research area with many applications in robotics, autonomous driving, augmented reality, and accessibility. It includes a range of tasks, such as video semantic and panoptic segmentation, depth estimation, object tracking among others. To advance this field, the community needs high-quality, large-scale datasets. In the last 10 years, growing interest in autonomous driving has resulted in the creation of several large-scale video datasets Kang et al. [2019], Mao et al. [2022], Wilson et al. [2023] that have panoptic segmentation masks, depth maps, camera poses, and other related annotations. However, outside of the autonomous driving domain, to the best of our knowledge, there is no publicly available video dataset annotated with both panoptic segmentation and depth maps. Autonomous driving datasets, though plenty, have limited generalization to egocentric human scene understanding. Videos taken from the human perspective have their own challenges, such as unorthodox viewpoints, motion artifacts, and dynamic or unpredictable interactions between other humans and objects in the scene. Unlike cars, humans operate in environments that are more cluttered, unpredictable, and less regulated. We believe that a comprehensive human egocentric dataset should not only help to build systems for related applications, but also *serve as a challenging benchmark for the scene understanding community*.

This work introduces **SANPO**, a dataset built to support research in outdoor human egocentric scene understanding. Although we focus on human navigation tasks, SANPO supports a wide variety of dense prediction tasks in outdoor environments and is challenging enough to be beyond the capabilities of current models. SANPO includes both real and synthetic data, with 112K and 113K video panoptic masks, respectively. It also includes 617K and 113K of real

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⁴https://google-research-datasets.github.io/sanpo_dataset/

⁵Synthetic data was provided by Parallel Domain.



Figure 1: **SANPO** is the only human-egocentric dataset with panoptic masks, multi-view stereo, depth, camera pose, and both real and synthetic data. SANPO has the largest number of panoptic frames among related work and a respectable number of depth annotations. (Note: ¹: multi-view, ²: partial coverage, ³: sparse depth)

and synthetic depth maps, respectively. The dataset was collected in various locations in the United States and covers different environments with varying weather conditions, times of day, and types of egomotion. Each real session also has videos from two stereo cameras, which can help to advance multi-view methods.

In addition to the dataset, we also set baselines for monocular depth estimation, semantic and panoptic segmentation, using state-of-the-art models.

2 Related Work

The closest publicly available datasets to ours are SCAND Karnan et al. [2022], MuSoHu Nguyen et al. [2023], and Ego4D Grauman et al. [2022], which are collected with a human egocentric perspective. SCAND is an autonomous robot navigation dataset collected with a front facing stereo camera, among other sensors, fitted on robots which are teleoperated. MuSoHu is collected with human ego motion with front facing stereo camera along with Lidar, microphone array and a 360° camera. SCAND and MuSoHu provide depth and odometry labels. MuSoHu also exhibits the camera motion artifacts caused by human motion. Ego4D is large and showcases a wide variety of activities. But MuSoHu, SCAND, and Ego4D lack semantic segmentation labels, and the first two are primarily developed for enabling robot navigation in social environments.

MOTSynth Fabbri et al. [2021] is another dataset that comes relatively close. It is a synthetic dataset for pedestrian detection and tracking, and it has both segmentation and depth annotations. However, this dataset has some limitations: (a) It only includes pedestrian segmentation and tracking annotations. (b) Only a small portion of the samples provide an egocentric view similar to what you would expect in egocentric human navigation.

Autonomous navigation is a well researched field Wen and Jo [2022], Shi et al. [2017] and the literature is teeming with various real-world Qiao et al. [2020], Kang et al. [2019], Wilson et al. [2023], Karnan et al. [2022], Nguyen et al. [2023], Cordts et al. [2016], Liao et al. [2022], Lin et al. [2014], Xu et al. [2018], Caelles et al. [2019], Brostow et al. [2009], Caesar et al. [2019] and synthetic datasets Mao et al. [2022], Richter et al. [2017], Fabbri et al. [2021]. The



Figure 2: **Data capture methodology for SANPO.** SANPO contains a mix of both real and synthetic data. The real data is captured from a chest-mounted camera and a head-mounted camera, while the synthetic data comes from a virtual environment. Our videos have depth maps and panoptic segmentations.

majority of the datasets available fall in either self driving car category Mei et al. [2022], Mao et al. [2022], Wilson et al. [2023], Cordts et al. [2016], Liao et al. [2022], Richter et al. [2017], Caesar et al. [2019], Pham et al. [2020] or general purpose scene understanding category Grauman et al. [2022], Lin et al. [2014], Xu et al. [2018], Caelles et al. [2019], Brostow et al. [2009]. The well known Cityscapes dataset Cordts et al. [2016], Qiao et al. [2020] is a daytime stereo video dataset with vehicle ego motion and segmentation & depth labels. Similarly, Wilson et al. [2023] is self driving car dataset with stereo video but with only 3D object detection labels. The datasets Richter et al. [2017], Mei et al. [2022], Mao et al. [2022], Brostow et al. [2009] are also self driving car video datasets with segmentation labels, except Mao et al. [2022], which includes 3D object detection labels instead.

Other existing datasets, such as MSCOCO Lin et al. [2014], DAVIS-2017 Caelles et al. [2019], and YouTube-VOS Xu et al. [2018], are either general-purpose scene understanding or domain-specific datasets, but they are not specifically designed for human navigation. MSCOCO Lin et al. [2014] is an image-based dataset, whereas DAVIS-2017 and Youtube-VOS Caelles et al. [2019], Xu et al. [2018] are video datasets. All of them are segmentation and/or object detection datasets but are not relevant to human navigation.

While there are many datasets available (see the supplementary material for an overview), there is a clear need for a challenging human egocentric dataset featuring unconstrained environments and comprehensive dense prediction annotations.

3 SANPO Dataset

SANPO dataset consists of two parts - SANPO-Real and SANPO-Synthetic. In this section we give an overview of both parts and describe how the dataset was collected and labeled.

3.1 SANPO-Real

This dataset consists of 701 sessions recorded from two stereo cameras simultaneously (thus each session has four RGB streams in total). Each video is approximately 30 seconds long with a frame rate of 15 frames per second (FPS). at 15 FPS. 597 sessions are recorded at a resolution of 2208×1242 pixels, and the remainder are recorded at a





Figure 3: **SANPO Real Sample.** Top row shows a stereo left frame from a session along with its ML depth and segmentation annotation. Bottom row shows the 3D scene of the session built using the annotations we provide. Points from several seconds of video are accumulated and aligned with ICP.

resolution of 1920×1080 pixels. We provided all videos in a lossless format to help facilitate stereo vision research. All videos were rectified using ZED software.

Each session is annotated with high-level attributes such as human traffic, vehicular traffic, number of obstacles, environment type, camera information and intrinsics, etc.⁶. Every stereo camera recording has camera poses provided by the ZED software using fused IMU and VIO measurements.

Each camera has both a sparse depth map from the ZED SDK and a dense depth map from CREStereo Li et al. [2022a], a recent ML-based stereo depth model. This model converts stereo frames to disparity maps⁷, which we then convert to depth using camera intrinsics and clip to 0-80 meters. Note that these CREStereo depth maps have a resolution of 1280×720 pixels; this is smaller than the RGB stream, but is the maximum resolution that pre-trained CREStereo supports Li et al. [2022a].

We provide semantic segmentation annotations for a of 237 videos: 146 long-range ZED 2i videos and not-from-samesession 91 wide-angle ZED M videos. Our segmentation taxonomy covers 31 categories: 15 *"thing"* classes and 16 *"stuff"* classes. We developed this taxonomy with a focus on egocentric scene understanding, balancing annotation practicality with the desire to be maximally useful for understanding the navigation environment.

A detailed taxonomy of these categories is provided in the appendix. The SANPO-Real dataset contains a total of 975,207 masks, including 195,187 human-annotated masks and 780,020 propagated masks (more details in the following section). Figure 3 shows an example of a SANPO-Real session.

⁶Please see the appendix for additional details.

⁷We compute disparity before blurring the sensitive information because blurry patches can create inaccurate or misleading results.



Figure 4: **Temporally Consistent Segmentation Annotation.** Top and bottom rows: Human-annotated segmentation masks for consecutive frames. Middle two rows: AOT-propagated segmentation masks for the intermediate frames (out of five) that were skipped during human annotation.

3.1.1 SANPO-Real Data Collection

In order to collect the real data, we designed a custom data collection rig (see supplementary material for details). Our volunteers wear a head-mounted ZED-M stereo camera and a chest-mounted ZED-2i stereo camera, as well as a backpack full of supporting hardware.

The chest-mounted ZED-2i captured 308,957 stereo frames with its 4mm lens, providing long range depth at a stable mounting point to mitigate motion blur. The lightweight head-mounted ZED-M provided wide range video and depth for 308,451 stereo frames. A team of volunteers collected data from various geographic locations across the United States covering different environments, including urban, suburban, city streets, and parks. Volunteers ran through different weather conditions (including snow and rain), times of the day (excluding low light conditions), ground types, obstacles, run/walk speeds, traffic levels, etc. We asked each volunteer to prefer diverse, dynamic scenarios and rare instances and events.

3.1.2 Panoptic Segmentation Annotation

Our segmentation annotation protocol is as follows: We divide each video into 30-second sub-videos and annotate every fifth frame for a total of 90 frames per sub-video. To make process more efficient and less error-prone we use two techniques. For dealing with a large number of classes we use cascaded annotation approach. We split all the labels in our taxonomy into five mutually exclusive subsets of co-occurring labels. A given sub-video is annotated for each subset in a prescribed order. When annotating a subset, all the annotations from the previous subset(s) are frozen and shown to the annotator. This approach helps reduce annotation of any missing regions from the previous subsets. We use AOT Yang et al. [2021] to both propagate masks from the previous frame to the next one during the annotation process and to infer the segmentation annotations for the intermediate frames, using the manually annotated preceding and following frames. This approach ensures that the annotations are temporally consistent for up to 30 seconds. We also provide information on whether each frame was annotated by a human or propagated by machine. The figure 4 shows an example of human annotated preceding and following frames along with the AOT propagated intermediate frames.

3.1.3 Privacy

All data collection is done in compliance with local, state, and city laws. Every volunteer was able to review each video in the data collection app before uploading it. All videos are processed to remove personally identifiable information (PII) such as faces and license plates before sending them for annotation.



Figure 5: **SANPO-Synthetic Sample.** Top row shows a single frame from a synthetic session along with its depth and segmentation annotation. Bottom row shows the 3D scene of the session built using the annotations we provide. Points come from the accumulated depth maps and camera locations across many frames.

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Figure 6: Synthetic vs real. A sample of SANPO-Real and SANPO-Synthetic data. *How quickly can you tell which of these images is synthetic*? Answer key in base64: 'c3ludGq6IEFCRUZILCByZWFsOiBDREdJ'

3.2 SANPO-Synthetic

Data captured and annotated under real-world conditions unfortunately has imperfect ground truth labels. These imperfections come from hardware (for example, motion blur), algorithms (i.e. depth from stereo), and human rating mistakes. Whereas, synthetic data has near perfect ground truth and can have any predefined properties. We partnered with *Parallel Domain* to supplement SANPO-Real with high-quality synthetic training and evaluation data. The synthetic environment was optimized to match real-world capture conditions as closely as possible, including camera parameters, placement and scenery. *SANPO-Synthetic and SANPO-Real are intended to be drop-in replacements for each other*, so researchers can study domain transfer tasks or take advantage of synthetic data during training without changing many domain-specific assumptions.

SANPO-Synthetic has 113,794 monocular and single-view video frames across 1961 sessions. 960 sessions are synthesized with a simulated chest-level ZED-2i camera and the other 1001 are taken with a simulated head-mounted ZED-M. Each virtual camera parameters match corresponding ZED camera parameters. Frame rate varies between 5 FPS, 14.28 FPS, and 33.33 FPS. Each synthetic video has dense depth maps and panoptic segmentation maps using the same taxonomy as SANPO-Real.

One advantage of synthetic data is its pixel-perfect instance segmentations, even with many small and distant instances. This is particularly beneficial for developing a challenging dataset to mimic the complexity of real-world scenes. *Over half of the synthetic frames contain* ≥ 60 *unique instance segmentations*, and a sixth of the data has ≥ 150 instances. Most of these masks are challenging: 80% of SANPO-Synthetic masks have less than 32^2 pixels, compared to 8.1% of masks in SANPO-Real. Instance IDs persist across frames and occlusions, which may be useful for tracking/reacquisition studies. Overall, there are 393,000 unique instance IDs in the synthetic data.

4 Experiments

In this section, we establish SANPO baselines in two evaluation settings:

- 1. Zero shot baseline: In this setting, we evaluate and report the generalization capability of published model checkpoints to SANPO dataset.
- 2. SANPO benchmark: We report and establish a baseline for a couple of state-of-the-art architectures on dense prediction tasks using SANPO dataset.

	Depth		Depth Prompt Based Instance Segmentation		Semantic Segmentation	
Dataset	DPT	ZoeDepth	SAM	Kmax-Deeplab ConvNeXt-L	Mask2Former Swin-L	
	RANSAC $\delta_{\leq 1.25}$ \uparrow		Instance mIoU↑	mIoU↑		
SANPO-Real	0.6703	0.6978	0.4896	0.3234	0.497	
SANPO-Synthetic	0.7955	0.8032	0.5121	0.4639	0.535	

Table 1: **Zero-shot evaluation.** In this setting, we evaluated the ability of state-of-the-art models trained on other relevant datasets to generalize to the SANPO test set for depth estimation and semantic segmentation. SANPO challenges these models' generalization capabilities.

4.0.1 Metrics

We report mean intersection over union (mIoU) and panoptic quality (PQ) for semantic segmentation and panoptic segmentation, respectively, as in Yu et al. [2023]. For depth, we report depth inliers ($\mathbb{E}\left[\max\left(\frac{y}{y'}, \frac{y'}{y}\right) \leq 1.25\right]$, denoted as $\delta_{\leq 1.25}$) as in Bhat et al. [2023]. All metrics are computed per image and then averaged over all images. Higher values are better for all metrics.

4.1 Zero shot evaluation

We intend for SANPO to be representative of outdoor human navigation tasks from an egocentric perspective. Humancentric tasks are distinct from other well-studied domains, such as autonomous driving. Our objective with this evaluation is to establish zero-shot baseline while evaluating how challenging our dataset is for zero-shot prediction. To this end, we evaluate various existing models on both depth estimation and semantic segmentation tasks.

For depth estimation, we used the publicly released checkpoints for DPT Ranftl et al. [2021] and ZoeDepth-M12 NK Bhat et al. [2023], which, according to the authors, were trained on a collection of both proprietary and public datasets. SANPO is a metric depth dataset, but for this zero-shot comparison, we found it necessary to give both these models the best possible advantage by calculating $\delta_{\leq 1.25}$ in a scale-invariant way: we used RANSAC to find alignment coefficients α, β that best aligned each image x with its groundtruth y; namely, $\arg \min_{\alpha,\beta} ||\alpha f(x) + \beta - y||^2$, taking $y' = \alpha f(x) + \beta$ as the output for each model.

For semantic segmentation, we used Kmax-Deeplab Yu et al. [2023] and Mask2Former Cheng et al. [2022] checkpoints trained on the Cityscapes dataset Cordts et al. [2016]. For a fair comparison, we mapped Cityscapes labelmap to the SANPO labelmap and excluded the SANPO classes (18 in total) that do not have a one-to-one correspondence. We do not report panoptic quality for this baseline because the SANPO "*thing*" labels differ from those of Cityscapes⁸.

We also included SAM Kirillov et al. [2023], a recent foundation model. For SAM, we used the center point prompt and reported instance-level mIoU, adhering to the conventional evaluation procedure for interactive segmentation Sofiiuk et al. [2022]. For the purpose of ensuring a streamlined evaluation process, we excluded very small instances which were less than 2% of image in size.

Our findings are summarized in Table 1. Overall, SANPO seems to be a challenging dataset for both depth and segmentation models. For example, DPT reports good depth estimation performance ($\delta_{\leq 1.25} > 0.9$) on KITTI, but we observe ~ 0.67 on SANPO-Real and ~ 0.8 on SANPO-Synthetic.

ZoeDepth Bhat et al. [2023] is designed to estimate metric depth for out-of-domain datasets, but still requires alignment on this data (unaligned $\delta_{\leq 1.25} \approx 0.2$ on SANPO-Real). The performance difference may be due to the lack of metric depth data available to the community. ZoeD-M12-NK was trained on total of 12 datasets, only two of which (NYUv2 and KITTI) are metric depth datasets.

On the segmentation side, Mask2Former (Swin-L) achieves an mIoU of 0.83 on Cityscapes validation set but ~ 0.49 on SANPO-Real.

In general, SANPO is a challenging and novel dataset that focuses on the domain of egocentric human navigation, with plenty of headroom.

⁸Details about the SANPO labelmap, its mapping to and from the Cityscapes labelmap, and the list of ignored labels are provided in the supplementary material.

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Figure 7: Segment Anything Model (SAM) on SANPO. We evaluated SAM on SANPO images. The middle column shows sample instance masks in SANPO and the selected point used to prompt SAM. The last column shows the predicted masks generated by SAM.

	Panoptic Segmentation				Depth	Estimation
Detect	Kmax-Deeplab-R50		Kmax-Deeplab-R50		BinsFormer	BinsFormer
Dataset	SAN	PO-Real	SANPO-Combined		SANPO-Real	SANPO-Combined
	mIoU↑	PQ↑	mIoU↑	PQ↑	δ	≤1.25 ↑
	Initialized with random weights					
SANPO-Real	0.3416	0.3173	0.3409	0.3210	0.4523	0.4702
SANPO-Synth	0.2735	0.2277	0.5549	0.4483	0.2744	0.8546
	Pretrained with Cityscapes				Pretrained wi	th Cityscapes-DVPS
SANPO-Real	0.4370	0.4298	0.4381	0.4234	0.4524	0.4862
SANPO-Synth	0.3900	0.3387	0.7109	0.5714	0.3235	0.8639

Table 2: **SANPO Benchmark.** Baseline performance of Kmax-Deeplab and BinsFormer, using ResNet-50 backbone, on SANPO for panoptic segmentation and depth estimation with limited training budget and standard hyperparameters.

4.2 SANPO Benchmark

In these experiments, we evaluated two state-of-the-art architectures: BinsFormer Li et al. [2022b] for depth estimation and Kmax-Deeplab Yu et al. [2023] for panoptic segmentation. Our objective is to establish baseline performance on the SANPO dataset for future research.

4.2.1 Experimental Setup

We trained the models on the SANPO train sets and evaluated them on the test sets. For the SANPO-Real experiments, we trained on \sim 494K samples from the SANPO-Real train set. We evaluated depth estimation on both the real and synthetic test sets. For panoptic segmentation, we trained on \sim 89K samples from the SANPO-Real train set and

evaluated on the SANPO real and synthetic test sets. For the SANPO-Combined experiments, we combined the SANPO-Real and SANPO-Synthetic train sets for training and used the test sets for evaluation.

We resized the data to 1025×2049 (with padding to maintain the aspect ratio) for training and evaluation. We trained two sets of models using a ResNet-50 backbone architecture:

- 1. Models initialized with random weights.
- 2. Models initialized with weights from models trained on the Cityscapes dataset for panoptic segmentation, and the Cityscapes-DVPS dataset ⁹ for depth estimation.

To ensure fair comparison and reproducibility, we limited the training budget to 50,000 steps with a batch size of 32 and used the standard hyperparameters as defined in Weber et al. [2021]. For reference, this training budget results in:

- 1. \sim 540 epochs of the Cityscapes panoptic segmentation dataset.
- 2. \sim 18 epochs of the SANPO-Real panoptic segmentation dataset.
- 3. \sim 3.3 epochs of the SANPO-Real depth estimation dataset.

Table 2 shows the baseline performance for panoptic segmentation and depth estimation on SANPO. Similar to the zero-shot evaluation, we observe that SANPO is a challenging dataset for both dense prediction tasks.

Additionally, we also observe, here and in the zero-shot experiments, that synthetic data has higher accuracy than real data. This performance gap between the real and synthetic sets could be attributed to two factors:

- 1. **Complexity of the environments & domain gap:** Real-world environments are more complex than synthetic data, with more variation in objects, backgrounds, and their interactions. The synthetic data also differs from the real data in appearance and lighting, although it can sometimes be hard to tell.
- 2. Accuracy of the segmentation annotations: Segmentation annotations are more precise in the synthetic data than in the real data.

Exact quantification of these factors would require additional domain adaptation experiments, which are beyond the scope of this work. We built the SANPO-Synthetic dataset to facilitate this line of research.

5 Conclusion

We presented the SANPO dataset, a large-scale video dataset for egocentric human navigation. It consists of 617k real stereo frames and 113k synthetic frames. All real frames have dense depth annotations, and $\sim 20\%$ of them have dense segmentation annotations. All synthetic frames have both depth and segmentation annotations. In addition to the depth and segmentation annotations, we also provide visual odometry readings (camera/ego-person poses).

This work also evaluated the dataset and presented benchmarks for cross-dataset zero-shot generalization and training on some state-of-the-art architectures. We hope that this dataset will help fellow researchers build visual navigation systems for the visually impaired and push the frontiers of visual scene understanding.

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A Dataset comparison

There are many outdoor video datasets created to study particular tasks ranging from robot navigation to autonomous driving to video segmentation and more. Tab. 3 compares our neighbors in this space. However, SANPO fills an important gap: to our knowledge, ours is the only human-egocentric dataset annotated with panoptic labels and depth maps that has both real and synthetic data.

A.1 Composition and statistics

Fig. 9 shows how often the high-level segmentation labels (described below) occur throughout SANPO imagery. Fig. 8 shows how many instances tend to occur in the real and synthetic portions of the dataset.



Figure 8: **Histogram of SANPO instance counts per image.** Real imagery tends to have fewer instances per image, with almost no real-world images having more than 40 annotated instances. Synthetic images, on the other hand, feature many more instances. This is because each object that populates the virtual world can have its own instance mask.



Figure 9: Semantic class occurrences in SANPO, shown as the fraction of frames that contain pixels labeled with each class. Common semantic classes like Building, Obstacle, Pole, Sky, and Tree appear in almost all frames. Other classes like Railway track, Bus stops, and Animal (including the horse that interrupted one volunteer in Central Park) are less common.

B Data Collection

Capture rig. Figure 10 shows all the all components and the assembled rig. The top row of images shows the system's components: (i) a backpack with ZED 2i and ZED-M cameras for data collection, (ii) the inside of the backpack showing the ZED box and battery pack mounted on a 3D printed container, and (iii) an Android app showing the live feed from the Zed cameras. The bottom row shows the system in use.

C Data Annotation

C.1 Session Attributes

Each real session is annotated with the following high level attributes.

1. Human Traffic

2. Vehicular Traffic

3. Number of Obstacles

Dataset	Domain	Environment	Quantity	# Sem Masks	# Depth Maps
SCAND Karnan et al. [2022]	er<	1 <u>n</u> + ²⁰⁰ / ₂₀₀	\sim 522 minutes		\sim 522 minutes
MuSoHu Nguyen et al. [2023]	e	<u>1∩1</u> + [§] . ⊙. ©.	\sim 600 minutes		\sim 600 minutes
Playing for Benchmark (Synthetic) Richter et al. [2017]	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	چ ب	250K frames	250K (Dense)	
Cityscapes-DVPS Qiao et al. [2020]	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	٤	3K frames	3K (Dense)	3K (Dense)
KITTI-360 Liao et al. [2022]	Ś	[%] ?	320K frames	2x78K (Dense) (left & right))	2x78K (Dense) (left & right))
Panoptic-nuScenes Caesar et al. [2019]	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	Â.	1.4M frames	40K (Dense & 3D)	
Waymo Open Dataset -Panoramic Mei et al. [2022]	Ś	پې بې	390K Frames	100K Frames	
A*3D Pham et al. [2020]	<u>ک</u>	چې بې	39K frames	39K (3D Bbox)	
ApolloScape-SceneParsing Huang et al. [2018]	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	چ ب	140K frames	140K (Dense)	140K (Dense)
DDAD Guizilini et al. [2020]	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	^ې	21K frames		21K (Dense)
DOLPHINS (Synthetic) Mao et al. [2022]	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	چ ب	42K frames	42K (3D Bbox)	
Argoverse2-Sensor Data Wilson et al. [2023]	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	کی + کی ا	1000 videos	3D Bbox	
CamVid Brostow et al. [2009]	\$ } }	ژب ب	5 videos	700 (Dense)	
Youtube-VOS Xu et al. [2018]	V.O.S.		\sim 340 minutes, \sim 20K frames	$\sim 4K$	
DAVIS-2017 Caelles et al. [2019]	V.O.S.		150 videos, 10K frames	10K	
MOTSynth (Synthetic) Fabbri et al. [2021]	Pedestrain Detection		1.3M frames	1.3M	1.3M
SANPO- Real	\$< };	ب	2x617K frames (left & right)	112K (Dense)	617K (Dense)
SANPO- Synthetic	\$ }	^{ېې}	113K frames	113K (Dense)	113K (Dense)

Image: Robot navigation, $\widehat{\begin{subarray}{c} < \\ \hline \begin{subarray}{c} < \\ \hline \begin{sub$

Table 3: SANPO is a unique video dataset that fills a gap in the existing landscape of video datasets. Most existing video datasets are focused on self-driving cars or general video object segmentation (VOS), and many of them are too constrained and not diverse enough. SANPO is the first dataset specifically focused on egocentric human navigation, and it has the following features: i) It is large-scale, challenging, and diverse. ii) It includes both real and synthetic data. iii) The real data is a multi-view stereo dataset.

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Figure 10: The SANPO data collection system for collecting real-world data. See text for details.

- 4. Environment Type
- 5. Weather Condition
- 6. Visibility
- 7. Speed of Ego motion
- 8. Elevation Change
- 9. Ground Appearances
- 10. Motion Blur

C.2 SANPO Taxonomy

Below SANPO taxonomy along with whether a class label is stuff or thing (i.e. with instance ids).

- 0. unlabeled \rightarrow stuff
- 1. road \rightarrow stuff
- 2. curb \rightarrow stuff
- 3. sidewalk \rightarrow stuff
- 4. guard rail/road barrier \rightarrow stuff
- 5. crosswalk \rightarrow thing
- 6. paved trail \rightarrow stuff
- 7. building \rightarrow stuff
- 8. wall/fence \rightarrow stuff
- 9. hand rail \rightarrow stuff
- 10. opening-door \rightarrow thing
- 11. opening-gate \rightarrow thing
- 12. pedestrian \rightarrow thing
- 13. rider \rightarrow thing
- 14. animal \rightarrow thing
- 15. stairs \rightarrow thing
- 16. water body \rightarrow stuff
- 17. other walkable surface \rightarrow stuff
- 18. inaccessible surface \rightarrow stuff
- 19. railway track \rightarrow stuff
- 20. obstacle \rightarrow thing
- 21. vehicle \rightarrow thing
- 22. traffic sign \rightarrow thing
- 23. traffic light \rightarrow thing
- 24. pole \rightarrow thing
- 25. bus stop \rightarrow thing
- 26. bike rack \rightarrow thing
- 27. sky \rightarrow stuff
- 28. tree \rightarrow thing
- 29. vegetation \rightarrow stuff
- 30. terrain \rightarrow stuff

C.3 Cityscape-19 \rightarrow SANPO Mapping

To ensure a fair comparison, we map Cityscape-19 labels to SANPO labels wherever possible. Below mapping from Cityscape-19 to SANPO taxonomy:

- 1. road \rightarrow road
- 2. sidewalk \rightarrow sidewalk
- 3. building \rightarrow building
- 4. wall \rightarrow wall/fence
- 5. fence \rightarrow wall/fence
- 6. pole \rightarrow pole

- 7. traffic light \rightarrow traffic light
- 8. traffic sign \rightarrow traffic sign
- 9. vegetation \rightarrow vegetation
- 10. terrain \rightarrow terrain
- 11. $sky \rightarrow sky$
- 12. person \rightarrow pedestrian
- 13. rider \rightarrow rider
- 14. car \rightarrow vehicle
- 15. truck \rightarrow vehicle
- 16. bus \rightarrow vehicle
- 17. train \rightarrow vehicle
- 18. motorcycle \rightarrow vehicle
- 19. bicycle \rightarrow vehicle

For all SANPO labels without an appropriate mapping from Cityscape-19, we treat the corresponding pixels as unlabeled and exclude them from the mIoU metric computation in the zero-shot experiments. The following SANPO labels were excluded:

- curb
- guard rail/road barrier
- crosswalk
- paved trail
- hand rail
- opening-door
- opening-gate
- animal
- stairs
- water body
- other walkable surface
- inaccessible surface
- railway track
- obstacle
- bus stop
- bike rack
- tree

D Evaluation

D.1 Zero-shot Mask2Former Evaluation

Mask2Former Swin-L model is reported to have mIoU semantic segmentation score 0.833 on Cityscapes validation set, but ~ 0.497 on SANPO-Real and ~ 0.535 on SANPO-Syn as reported in the Table 4. Fig 11 shows qualitative evaluation on a SANPO synthetic and real sample.

D.2 SANPO SAM Evaluation

We have captured very fine details with high quality, exemplified by semantic masks for even the smallest instances within the image. Some examples are shown in Fig 12. As an image can have many such instances, therefore, in order to streamline our experiment with SAM on SANPO we report evaluation with masks of size greater than 2% of the image area.



Figure 11: **Mask2Former Zero Shot Evaluation.** An egocentric human navigation needs to accurately distinguish between road and sidewalk (a walkable surface), as one is not safe for human navigation and the other is safer. The top row (SANPO synthetic sample) and the bottom row (SANPO real sample) demonstrate how Mask2Former (trained on Cityscapes) confuses sidewalk as road. The visualization is generated with Mask2Former tool.

	mIoU		
Labels	SANPO-Real	SANPO-Synthetic	
road	0.255	0.407	
sidewalk	0.120	0.262	
building	0.642	0.934	
wall/fence	0.448	0.087	
pedestrian	0.679	0.878	
rider	0.271	0.247	
vehicle	0.658	0.817	
traffic sign	0.212	0.240	
traffic light	0.127	0.344	
pole	0.310	0.586	
sky	0.658	0.919	
vegetation	0.654	0.303	
terrain	0.394	0.166	
Average mIoU	0.497	0.535	

Table 4: Mask2Former Zero-Shot Evaluation: Per label breakdown of mIoU on the Mask2Former zero-shot experiment.

D.3 SANPO qualitative examples

We show some example images in Fig. 13, as well as ground truth and predicted segmentation maps from kMax-Deeplab and ground truth and predicted depth maps from Binsformer.

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SANPO Image (left) and Mask (right)

Figure 12: **SANPO images and masks with fine details.** Right column shows masks (purple) even for the smallest instances within the images.



Figure 13: **Qualitative examples on SANPO**, showing (left to right): image, groundtruth and predicted segmentation maps, and groundtruth and predicted depth maps.