DiVA-360: The Dynamic Visuo-Audio Dataset for Immersive Neural Fields

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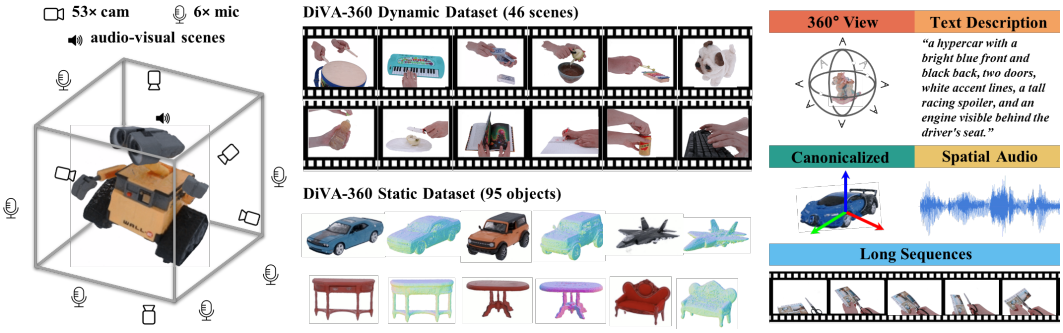

Figure 1: DiVA-360 is a **real-world** 360° multiview audio-visual dataset of dynamic and static scenes captured using a table-scale capture system consisting of 53 RGB cameras and 6 microphones. The DiVA-360 **dynamic** dataset consists of 46 prolonged (5s to 3 mins) dynamic scenes and interactions, while the DiVA-360 **static** dataset contains 95 objects across 11 categories and 30 static multi-object scenes. We also provide detailed text descriptions, 6 degrees of freedom (DoF) object pose canonicalization, spatial audio, and foreground-background segmentation. The goal of DiVA-360 is to enable continued progress in multimodal audio-visual neural field research.

Abstract

Advances in neural fields are enabling high-fidelity capture of the shape and appearance of static and dynamic scenes. However, their capabilities lag behind those offered by representations such as pixels or meshes due to algorithmic challenges and the lack of large-scale real-world datasets. We address the dataset limitation with DiVA-360, a real-world 360° dynamic visuo-audio dataset with synchronized multimodal visual, audio, and textual information about table-scale scenes. It contains 46 dynamic scenes, 30 static scenes, and 95 static objects spanning 11 categories captured using a new hardware system using 53 RGB cameras at 120 FPS and 6 microphones for a total of 8.6M image frames and 1360 s of dynamic data. We provide detailed text descriptions for all scenes, foreground-background segmentation masks, category-specific 3D pose alignment for static objects, as well as metrics for comparison. Our data, hardware and software, and code are available at `https://diva360.github.io/`.

1 Introduction

Neural fields [78], or neural implicit representations, have recently emerged as useful representations in computer vision, graphics, and robotics [78, 67] for capturing properties such as radiance [46, 5, 4], shape [50, 81, 73, 49, 43, 38], dynamic motion [71, 35, 77, 20, 40, 7, 53], audio [41], and

language [32]. Their high fidelity, continuous representation, and implicit compression [19] properties make them attractive for immersive digital representation of our world.

However, despite their popularity, neural field capabilities remain far from that of conventional representations such as pixels (in 2D), and point clouds or meshes (in 3D). For instance, we can watch hours of videos with synchronized audio online, we can animate 3D meshes quickly on any device, and we have methods to quickly align 3D point clouds – tasks that currently cannot be achieved with neural fields. Recent work aims to enable these capabilities with most of it focusing on methods and algorithms [24, 79, 2] but **large-scale, real-world** datasets and benchmarks are equally important for continued progress [18, 13, 70, 8]. While some static [28, 55, 45, 75] and dynamic datasets [35] exist for neural fields, they have several limitations. First, existing dynamic datasets are limited to only a few scenes and only a few forward-facing cameras capturing for short durations. Second, static datasets may contain numerous objects and categories but lack within-category 3D alignment (aka *canonicalization*) – a common feature of synthetic 3D datasets like ShapenetCore [9, 56] that facilitates category-level learning [51, 66, 44, 25]. Third, many real-world datasets are captured with moving monocular cameras that cannot always provide sufficient multi-view cues for immersive reconstruction [21, 38, 53]. Finally, none of these datasets contain visually-adjacent modalities like audio and text similar to synthetic datasets [22, 23, 17].

We address these limitations by presenting **DiVA-360**, a real-world 360° dynamic visuo-audio dataset that contains synchronized multimodal visual, auditory, and textual information about table-scale objects and interactions. Rather than focus on the number of objects/scenes and categories, we instead focus on rich high-quality, synchronized, multimodal data about static and dynamic scenes. Our dynamic data includes high-resolution (1280×720), high-framerate (120 FPS), long (5s to 3 mins), and audio-synchronized videos captured simultaneously from 53 RGB cameras and 6 microphones spanning 360° volume within the capture space. Our static data includes high-resolution 53-view images and category-specific 6 degrees of freedom (DoF) pose alignment for object instances. Both static and dynamic scenes contain detailed text descriptions and foreground-background segmentation masks. In total, we provide **46 prolonged dynamic objects and interactions** spanning **1,360** seconds, **8.6M image frames**, **30 static multi-object scenes (5 clean and 25 messy)**, and **95 static objects from 11 categories**, all annotated with **8632 words of text descriptions** (see Table 2).

Capturing such large-scale multimodal data requires advances in capture systems, as well as benchmarking metrics. We have built a new capture system called **TRICS (Temporal Interaction Capture System)** which is designed to meet the multi-sensor synchronization, high-framerate, high-fidelity, and lighting requirements. For both the dynamic and static datasets we propose standardized metrics for reconstruction quality and runtime, and compare baseline methods on these metrics [47, 71]. Our datasets, capture system, metric computation code, and annotations will be made publicly available to the community at `https://diva360.github.io/`. To summarize, we make the following contributions:

- **TRICS**: A capture system specifically designed for 360° audio-visual capture of table-scale static and dynamic scenes with 53 RGB cameras and 6 microphones. We have developed our own hardware and software for sensor synchronization, capture, transfer, and calibration.
- **DiVA-360 Dynamic Dataset**: The largest audio-visual dataset for dynamic neural fields with 46 sequences (5s to 3 mins) captured at 120 FPS with synchronized spatial audio.
- **DiVA-360 Static Dataset**: We present a large static dataset of 30 scenes and 95 real-world objects spanning 11 categories captured in a category-aligned orientation and another random pose. This dataset includes information about the 6 DoF pose of objects.
- **Annotations**: For both dynamic and static scenes, we provide foreground-background segmentation masks, detailed text descriptions, trained models, and other metadata.

We believe our work can help the community take a leap from the current focus on static scenes and short dynamic videos toward a more holistic understanding of longer dynamic scenes, as well as text-to-4D scene generation [62], 3D object canonicalization [2], and audio-visual robotics [11].

2 Related Work

Neural Fields: Neural fields, coordinate-based neural networks, have generated considerable interest in computer vision [78] because of their ability to represent geometry [44, 50, 12] and appearance [46, 40, 63]. Neural radiance field (NeRF) [46] utilizes a Multilayer Perceptron (MLP) to model density and color, leading to photorealistic novel view synthesis. Extensions of NeRF have also been used to model shape with high-fidelity [81, 49, 37, 71]. Meanwhile, several methods have made efforts to reduce the cost of constructing NeRF models [47, 59, 10]. Naturally, some approaches have also turned their focus towards dynamic neural fields [71, 35, 53, 38, 52, 54, 20, 40]. However, these methods have thus far been limited to brief sequences and inadequate scene view due to the limited camera capture range of the training data. A promising direction being explored is the incorporation of audio and language modalities [41, 32, 26] with neural fields. Our work aims to facilitate the broad spectrum of neural field research with a more comprehensive and richer dataset, from higher-fidelity rendering to faster training for 4D dynamic field and from visual to multimodal visual-audio-textual learning.

Type	Dataset	Real	360° view	Dynamic	Caption	Canonical	Audio
Scene	DTU[27]	✓	✓	✗	✗	—	✗
	BlendedMVS[80]	✗	✓	✗	✗	—	✗
	ScanNet[13]	✓	✗	✗	✗	—	✗
	LLFF[45]	✓	✗	✗	✗	—	✗
	Mip-NeRF 360[5]	✓	✓	✗	✗	—	✗
	Block-NeRF[65]	✓	✗	✓	✗	—	✗
	DyNeRF[35]	✓	✗	✓	✗	—	✗
	HyperNeRF[53]	✓	✗	✓	✗	—	✗
	NDSD[82]	✓	✗	✓	✗	—	✗
	ILFV[7]	✓	✗	✓	✗	—	✗
	Deep3DMV[39]	✓	✗	✓	✗	—	✗
Object	ShapeNet[9]	✗	✓	✗	✗	✓	✗
	NeRF[46]	✗	✓	✗	✗	✓	✗
	CO3D[55]	✓	✓	✗	✗	✗	✗
	ScanNeRF[14]	✓	✓	✗	✗	✓	✗
	OmniObject3D[75]	✓	✓	✗	✗	✓	✗
	ObjectFolder[23]	✗	✓	✗	✗	✓	✓
Hybrid	PeRFception[28]	✓	✓	✗	✗	✗	✗
	Objaverse[17]	✗	✓	✓	✓	✓	✗
	DiVA-360	✓	✓	✓	✓	✓	✓

Table 1: We compare featured properties of our DiVA-360 with other multiview object-centric and scene-centric datasets. Our real-world 360° view dataset features the most comprehensive modalities and rich annotations of both static objects and dynamic scenes, aimed at promoting research in dynamic neural fields and 3D multimodal learning.

Multi-Camera Capture Systems: Capturing rich multimodal data requires hardware and software systems for capturing rich data. The earliest multi-camera capture systems were extensions of stereo cameras to 5–6 cameras [30] which were later extended to capture a hemispherical volume [31] with up to 50 cameras for 3D and 4D reconstruction using non-machine learning techniques [68]. Multi-camera systems have also been combined with controllable lights to build *light stages* [16, 15]. Recent examples of multi-camera capture systems include the panoptic camera systems [29, 29, 83]. Specialized systems have been built for table-scale interactions, notably for hand interaction capture [85, 6]. However, these systems have a limited number of cameras. Our TRICS system is specially designed for dense 53-view audio-visual capture of table-scale scenes while also acting as a light stage.

Large 3D Datasets: Past advances in 3D learning have been largely driven by synthetic datasets such as ShapeNet [9] and ModelNet [76], but their utility is somewhat curtailed by the absence of a realistic appearance. Datasets for NeRF [46, 5], LLFF [45], and multiview Stereo (MVS) research (DTU [1], Tanks & Temples [34], and BlendedMVS [80]) have provided sufficient multiview images, yet their application is constrained to static scenes. Datasets like CO3D [55], OmniObject3D [75], and ScanNeRF [14] and derivates like PeRFception [28] also focus on static objects and additionally lack consistently orientation for objects.

Regarding dynamic datasets, BlockNeRF [65] contains hundreds of videos of street views, incorporating dynamic elements like cars and pedestrians but lacks a focus on objects, is short, and lacks multiple views. DyNeRF [35], NDSD [82], ILFV [7], and Deep3DMV [39] use multiple forward-facing cameras to take videos of dynamic activities so they lack views from behind. Besides, DyNeRF and ILFV only contain short clips mostly around 10 s. Monocular dynamic view synthesis datasets [53, 38, 52] capture monocular videos of human faces and human activities. However, the use of a single camera restricts the visibility of all dynamic components from multiple viewpoints

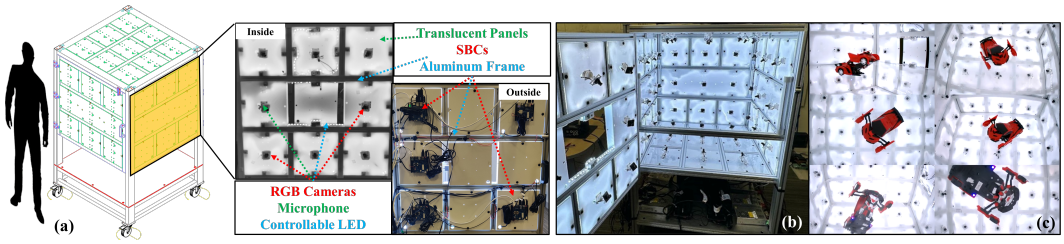

Figure 2: (a) TRICS is a refrigerator-sized aluminum frame that supports a $1m^3$ capture volume mounted on wheels for mobility. Each side wall of the capture volume is divided into a 3×3 grid with each grid square containing sensors, LEDs, single-board computers (SBCs), and light diffusers. (b) Two walls of the capture volume act as doors for easy access to the capture volume. (c) We can acquire 360° RGB views of dynamic and static objects in this capture volume (6 views shown).

simultaneously, resulting in low effective multi-view factors (EMF)[21]. It is worth noting that Objaverse [17] has created a substantial collection of top-tier 3D object models, characterized by their wide-ranging categories and detailed annotations, inclusive of text descriptions and tags. Alongside this, they introduced animated sequences to portray dynamic scenes. However, their data is not sourced from the real world. Our dataset stands out by offering a 360° view of real dynamic scenes with spatial audio and static objects captured in a consistent orientation within each category, all of which are annotated with rich text descriptions (see Table 1).

3 Temporal Interaction Capture System (TRICS)

Our goal is to capture rich multimodal data of table-scale objects and interactions to enable further research in high-fidelity audio-visual neural fields. To achieve this, we need a hardware and software system that can capture high-framerate, high-resolution video and audio, and have the capability to synchronize and calibrate these sensor streams. While commercial products exist for this purpose, they do not meet all of our requirements. We therefore designed and built our own hardware and software solution which we call the **Temporal Interaction Capture System (TRICS)**. Figure 2 shows our hardware system for capturing synchronized multimodal data. Please see the supplementary document for more extensive details.

TRICS Hardware: Our system uses a mobile aluminum frame, housing a $1m^3$ capture volume outfitted with sensor panels across a 3x3 grid on each of its six sides (Figure 2 (a)). These panels consist of RGB cameras, microphones, and programmable LED light strips, which together create a versatile and uniformly light environment. The system is designed to handle large data output through a custom communication setup that compresses and transmits data to a high-capacity control workstation. This design, combining portability, comprehensive capture capabilities, and efficient data management, allows for dynamic, 360° view capturing with low latency.

TRICS Software: While our hardware allows the capture of large-scale rich multimodal data, controlling the sensors and LEDs, synchronizing and managing data, and camera calibration requires specialized software which we have developed. For camera and microphone synchronization, we adopt network-based synchronization [3] with an accuracy of 2–3ms. For camera calibration, during each capture session, we affix transparent curtains with ArUco markers to the walls. Using COLMAP [60, 61], we generate camera poses for the 53 cameras. The camera poses are further refined using Instant-NGP's [47] dense photometric loss for improved reconstruction quality. Finally, we also built software for efficiently transferring terabytes of data from the control workstation to cloud storage. We will release all of our software for community use.

4 DiVA-360 Dataset

We now describe our multimodal dynamic and static datasets that have been captured using TRICS. While other datasets have focused on in-the-wild capture and a large number of categories [28, 55],

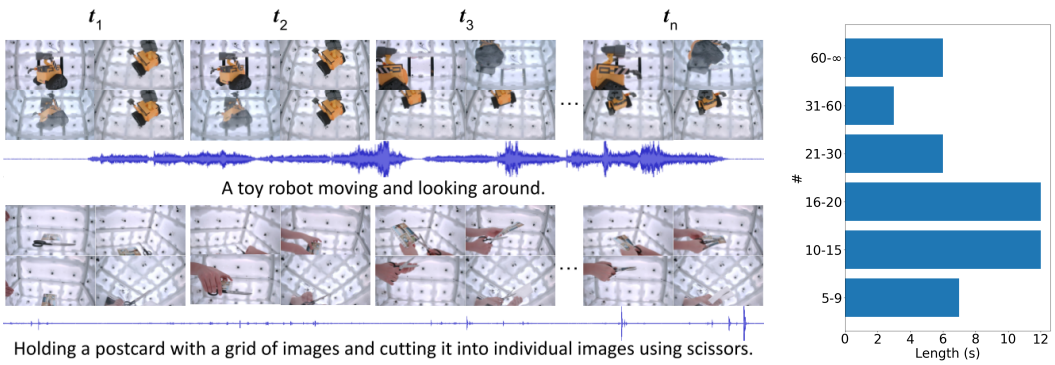

Figure 3: The DiVA-360 dynamic dataset contains multiview images and audio of dynamic objects (top row) and scenes (bottom), including routine human activities, musical instrument play, and objects moving or playing themselves. Our audio component (displaying 1 of 6 channels) contains both loud (e.g., top) and more subtle sounds (e.g., bottom) of objects in motion. On the right, we show the duration distribution of our sequences.

our goal is to focus on rich synchronized and multimodal data at high resolution, framerate, spanning long duration, and captured from all 360° volume within the capture space. Our dataset contains 8.6 M image frames of 46 prolonged dynamic scenes over 1360 seconds, 95 static objects across 11 categories, and text descriptions totaling 8632 words.

4.1 Dynamic Dataset

The DiVA-360 dynamic dataset contains synchronized long-duration audio-video of both moving objects and hand interactions. Our goal is to make this dataset useful for learning long-duration dynamic neural fields of appearance and audio – existing methods have been limited to only short durations and lack audio [35, 71]. We captured 21 dynamic objects and 25 hand interactions with objects for a total of 1360 seconds of audio-visual data from TRICS (see Figure 3). Our data also contains masks for foreground-background segmentation and detailed text descriptions of each sequence. To our knowledge, this is the largest-scale multimodal audio-visual dynamic dataset.

Dynamic Objects: We selected 21 dynamic objects that move and produce sounds. To be representative of real-world motions, we chose scenes with different types of motion: (1) Slow motion: objects that perform slow, continuous motions, e.g., music box and rotating world globe. (2) Fast motion: objects that move or transform drastically, e.g., remote control cars and dancing toys. (3) Detailed motion: objects that perform precise motions, e.g., a clock. (4) Repetitive motion: objects that repeat the same motion pattern, e.g., Stirling engine and toys that sway left and right. (5) Random motion: objects that perform indeterministic motions, e.g., plasma ball and sand in an hourglass. During capture, all objects are placed on a transparent shelf for 360° view.

Interactions: In addition to dynamic objects, we also include 25 hand-object interaction scenes representing real-world activities. The interactions included are hand activities commonly observed in everyday life, such as flipping a book, replacing a toy's batteries, and opening a lock. Most interactions also generate subtle sounds, such as turning a page or opening a soda can. We hope these hand-centric interactions encourage future modeling of complex hand dynamics. Similar to dynamic objects, the objects to be manipulated are placed on a transparent shelf.

Text Descriptions: Each dynamic scene is accompanied by natural language descriptions at 3 levels of detail. These descriptions are generated entirely by a human annotator without the assistance of any automated tools. As such, we provide a human baseline for tasks that aim to align 3D visual representations with natural language. The coarsest level aims to capture a broad summary of the scene ("putting candy into a mug"), while finer levels increasingly describe appearance ("...the pieces are in pink, green, orange, and black wrappers..."), relative position ("...candy scattered around a black mug..."), number of hands, audio, and temporal progression. Across all 46 dynamic scenes, the

average length of the descriptions is 6.1, 18.4, and 38.7 words for the 3 levels of detail, amounting to a total of 2907 words.

Foreground-Background Segmentation: A major challenge in our dataset is the segmentation of foreground objects from background clutter. Manually segmenting every frame is infeasible due to the quantity and view inconsistency. Therefore, we developed a segmentation method using Instant NGP [47]. As preparation, we manually segment the foreground object in the first frame of one scene and train an I-NGP model on segmented images to refine coarse camera poses extracted from COLMAP[60, 61]. The refined pose is used for all downstream tasks. For each frame, we fit an I-NGP model that optimizes camera poses, lens distortion, and image latent vector. The model's bounding box is then progressively reduced to remove background clutter. We then render trained I-NGP as binary masks. To further refine the masks, we removed connected components smaller than a threshold. Segmenting with this method is possible because all objects are placed around the center of TRICS. Since the segmentation is generated from I-NGP, the masks are multi-view consistent.

We analyze and compare the our DiVA-360 dynamic dataset with other dynamic datasets and two large object-centric datasets in Table 2. DyNeRF [35] consists of only 6 short clips of forward-facing scenes. Block-NeRF [65] captures a single long video of a street view from a moving vehicle. This creates fleeting scenes that do not encompass full 360° camera coverage. Though Objaverse offers an expansive repository of animations, it lacks real-world scenes resulting in a domain gap. Our dataset incorporates extensive, prolonged dynamic sequences from 53 different viewpoints, effectively eliminating any blind spots within the dynamic components of the scene. In Section 5, we show how this data can be used to study dynamic neural field models and we provide metrics for comparison. We believe our synchronized audio and video data will spur new research.

	Object		Dynamic Scene		
Dataset	**#Objects**	**#Categories**	**#Scenes**	**#Frames**	**Average length (s)**
CO3D[55]	19k	50	—	—	—
OmniObject3D[75]	6k	190	—	—	—
Objaverse[17]	818k	21k	3k	∞	—
DyNeRF[35]	—	—	6	37.8k	10
HyperNeRF[53]	—	—	17	13.8k	27
Deep3DMV[39]	—	—	96	3.8M	33
ILFV[7]	—	—	15	270.4k	13
Block-NeRF[65]	—	—	1	12k	100*
DiVA-360	95	11	46	8.6M	29.6

Table 2: Specifications of our DiVA-360 dataset and other dynamic datasets and large-scale object-centric datasets. $*$ indicates that despite Block-NeRF comprising a 100s-long video, it is made up of numerous transient street scenes, each with restricted view coverage.

4.2 Static Dataset

The DiVA-360 static dataset contains 360° 53-view images of 95 objects spanning 11 categories captured at two orientations, and 30 multi-object scenes captured (5 clean and 25 messy). Our goal is to make this dataset useful for categorical neural field learning for real-world objects. This dataset also contains language descriptions for each object instance at 3 levels of detail. Finally, to support category-level 3D learning, we provide the 6 degrees of freedom (DoF) pose of all object instances. In total, this data contains 11,660 images and 5725 words of text descriptions (see Figure 4).

Objects: The static dataset contains categories of objects similar to those found in ShapeNet [9] (e.g., cars, airplanes, cabinets), as well as common objects found in everyday life (e.g., utensils, mugs, keyboards). We also collected 30 multi-object scenes to resemble miniature rooms in both cluttered and cleanly-arranged settings [74]. For single objects, we first capture them in a pre-specified category-level canonical orientation followed by a random orientation. Similarly, for multi-objects, we first capture them in a "clean" state and rearrange the objects to capture increasingly messy states.

Text Descriptions: As in the dynamic dataset, we provide the natural language descriptions of the objects at 3 levels of detail generated entirely by a human annotator. For these static objects, the coarsest level provides a brief, generic description ("a black car"), while finer levels introduce details in appearance ("an all-black muscle car...") and aim to differentiate the object within its class ("...with

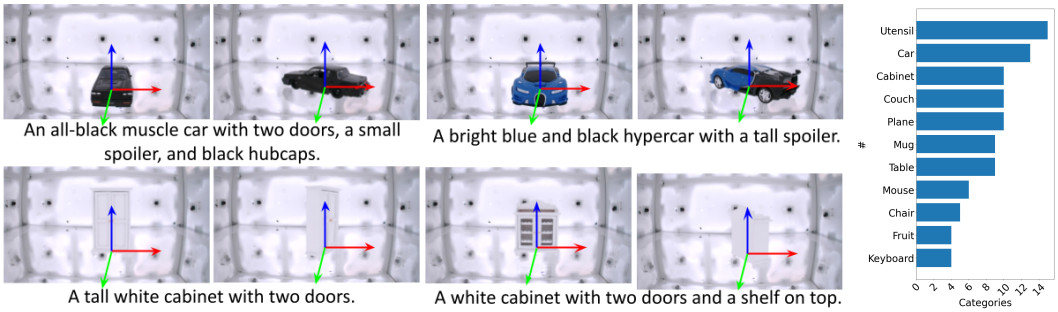

Figure 4: We showcase 4 pairs of captured static objects in a pre-defined canonical pose (left) and random poses (right) for each category. The histogram on the right shows our dataset includes a variety of objects from common shape categories.

two doors..."). Across all 125 static scenes, the average length of the descriptions is 4.8, 10.9, and 30.2 words for the 3 levels of detail, amounting to a total of 5725 words.

Canonicalization: We provide category-level canonicalization for each of the static object categories, which provides an equivariant frame of reference that is consistent in position and orientation (3D pose) at the category level [56]. We automatically canonicalize objects using Canonical Fields Network (CaFi-Net) [2]. CaFi-Net uses a Siamese network architecture to extract equivariant field features from the neural field of object instances in arbitrary poses, and estimate a transformation that maps input to a canonical pose. We use CaFi-Net because of its self-supervised nature to estimate the canonical pose of each category.

While the scale of objects and categories in our dataset is smaller compared to CO3D and OmniObject3D, it compensates with rich textual annotations, and each object category is consistently presented in a canonical pose, which facilitates the learning of category-level 3D representations. We hope that our DiVA-360 static dataset will accelerate research in object-centric learning in neural fields. In Section 5, we show how this data can be used to evaluate methods for static neural field reconstruction and provide metrics for 6 DoF pose canonicalization.

5 Benchmarks & Experiments

We show how DiVA-360 can be used to as a benchmark for neural field methods. We propose to standardize metrics for comparisons across methods and provide results of baselines on these metrics. All our experiments use Nvidia GPUs (2080Ti, 3090, 4090, A5000) for training and evaluation.

5.1 DiVA-360 Dynamic

Our goal is to evaluate existing methods for dynamic neural field reconstruction on image reconstruction quality. Specifically, we choose to compare two methods: (1) MixVoxels [71], a state-of-the-art method designed for dynamic radiance field reconstruction, and (2) Per-Frame I-NGP (PF I-NGP) [47], a static NeRF model which we fit to individual frames in all 46 sequences.

Pre-processing: We downsample the videos to 30 FPS and then segment all frames following Section 4. We select the top 35 out of 53 best cameras for training and hold out 6 cameras for testing.

Metrics: We use (a) Peak Signal-to-Noise Ratio (PSNR), (b) Structural Similarity Index Measure (SSIM) [58, 69], (c) Learned Perceptual Image Patch Similarity (LPIPS) [84] to measure the rendering quality, and Just Objectionable Difference (JOD) [42] to measure the visual difference between rendered video and ground truth, along with per-frame training/rendering time (s) for 6 testing views.

Results and Analysis: We quantitatively compare the two baseline methods MixVoxels and PF I-NGP in Table 3. Since PF I-NGP fits each frame individually and has more network capacity, its overall reconstruction performance is better than MixVox-

Baseline	PSNR↑	SSIM↑	LPIPS↓	JOD↑	Train (s/f)↓	Render (s/f)↓
MixVoxels[71]	27.39 ± 2.35	0.94 ± 0.02	0.09 ± 0.03	7.53 ± 1.09	66.33 ± 43.19	1.77 ± 0.52
PF I-NGP[47]	28.13 ± 3.50	0.95 ± 0.03	0.08 ± 0.04	7.61 ± 0.93	48.85 ± 4.73	0.67 ± 0.18

Table 3: We compare the rendering quality and train/render time of MixVoxels and PF I-NGP for dynamic scenes. Not surprisingly, PF I-NGP achieves higher rendering quality as it trains a model for each individual frame, though it lacks temporal coherence. In contrast, MixVoxels exhibits a much more compact form. The time is measured in seconds per frame (s/f).

els (see Figure 5 and Figure 6). However, MixVoxels only requires 2.7-4.7 MB storage space per time step, which is six times smaller than PF I-NGP's 29 MB. Surprisingly, although MixVoxels is designed for dynamic scenes, its training and inference times are higher than PF I-NGP (with a higher variance). Besides, we also notice that MixVoxel struggles to capture the dynamic components of the scenes, leading to blurry and noisy reconstruction (Figure 6 bottom). In the supplement, we provide more details on the differences between the methods for various scenes. Our primary objective is to establish initial baseline and serve as a resource for future research aimed at enhancing these aspects.

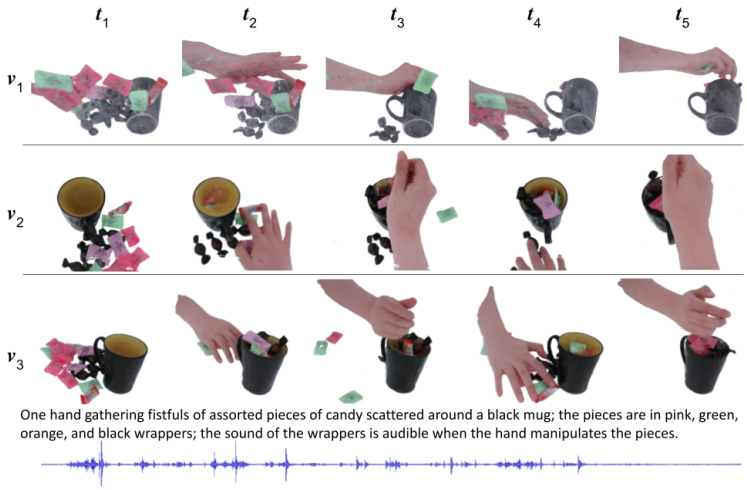

Figure 5: **Qualitative results of PF I-NGP on dynamic scene.** We show 3 views, 5 timestamps, text descriptions, and 1 audio channel. PF I-NGP has good per-frame quality but lacks temporal consistency.

5.2 DiVA-360 Static

To help build neural field representation for entire categories of objects, our dataset provides canonical-oriented objects, which helps category-level understanding and generalization [64, 36, 48, 72, 57]. We use our object data captured in both canonical pose and random poses to benchmark neural object canonicalization methods [2] to facilitate future research in category-level 3D perception. We also provide a benchmark for rendering quality using I-NGP [47].

Pre-processing: We segment objects using the Segment Anything Model (SAM) [33] followed by fitting an I-NGP model (Section 4).

Metrics: We train I-NGP on 34 best views and validate on 6 held-out views. We use the same PSNR, SSIM [58, 69], LPIPS [84] metrics for evaluation. We provide a benchmark on categorical neural object canonicalization using CaFi-Net [2]. For evaluation, we use the Instance-Level Consistency (IC) and Category-Level Consistency metrics [56].

Categories	CC ↓	IC ↓	Categories	CC↓	IC ↓
chair	0.0411	0.0203	keyboard	0.1396	0.0719
table	0.0630	0.0292	car	0.0626	0.0224
cabinet	0.0736	0.0374	couch	0.0604	0.0343
mouse	0.0443	0.0494	plane	0.0538	0.0443
utensil	0.1536	0.1134			

Table 4: Object canonicalization benchmark using CaFiNet [2]. The performance is reasonably well for structured shapes such as chairs and tables but it struggles with smaller shape such as utensils.

Results and Analysis: In Table 5, we notice that some category has much better results than others leaving room for future improvements. Furthermore, segmentation artifacts appear in some scenes

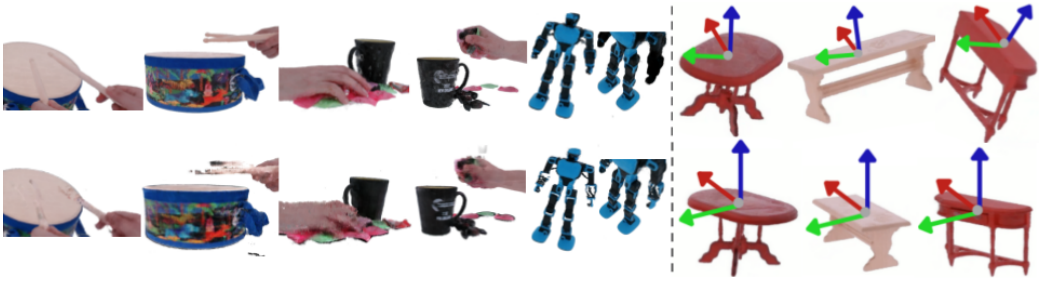

Figure 6: **Qualitative comparison of PF I-NGP and MixVoxels and results on CaFiNet[2].** We show rendering from PF I-NGP (top) and MixVoxels (bottom) on the left and show canonicalization results on the right (top: randomly oriented table NeRFs, bottom: canonicalized tables). MixVoxels frequently generates artifacts like floaters or holes, particularly in the most dynamic components such as drumsticks and hands.

Category	PSNR ↑	SSIM* ↑	LPIPS* ↓	Category	PSNR ↑	SSIM* ↑	LPIPS* ↓
Chair	32.95±2.11	98±0.9	5±2.3	Keyboard	31.57±1.58	97±0.8	7±1.0
Table	38.11±1.88	99±0.3	2±0.6	Car	34.06±1.40	98±0.4	3±0.5
Cabinet	38.02±1.65	99±0.3	3±0.8	Couch	32.87±1.51	98±0.6	4±0.9
Mug	32.98±2.12	98±0.6	4±0.7	Plane	34.04±3.30	98±0.8	4±2.1
Fruit	34.91±2.36	99±0.3	3±0.8	Utensil	36.45±3.19	99±0.4	6±2.9
Mouse	35.03±2.40	99±0.2	3±0.4	Scenes	27.41±2.48	95±2.0	8±2.7

Table 5: Rendering quality for static object categories and scenes using Instant-NGP [47]. Metrics with (*) are multiplied by 10^2 to accommodate space. Notice that some categories perform better than others, suggesting future methods that better generalize to a variety of shapes.

with more intricate and detailed geometries, encouraging future work in neural surface reconstruction. The training time for each object instance was 60.51 s (35,000 iterations), and the mean rendering time for 6 validation views was 0.29 s per frame. Table 4 shows the results of canonicalization performance on various categories (we exclude two categories with few instances). CaFi-Net shows good performance on categories with structured 3D shapes (e.g., tables) and sufficient instances.

6 Conclusion

We have introduced DiVA-360, a real-world 360° dynamic visuo-audio dataset that contains synchronized multimodal visual, auditory, and textual information about table-scale objects and interactive scenes. We propose a new TRICS capture system for rich multimodal data capture. DiVA-360 consists of a dynamic dataset of high-resolution, high-framerate, long (5s to 3 mins), and audio-synchronized videos captured simultaneously from 53 RGB cameras and 6 microphones spanning 360° volume within the capture space. Our static data similarly includes high-resolution 53-view images and category-specific 6 DoF pose alignment for object instances. In addition, both static and dynamic scenes contain detailed text descriptions of the scene or interaction and mask annotations to separate the foreground from the background.

Limitations and Future Work: Our focus is intentionally on high-quality multimodal data rather than the number of scenes or objects, but large-scale learning is also essential and provided by datasets like [55, 75]. Our metrics and evaluation are limited to images – in future work we will consider metrics for audio and text. TRICS cannot capture scenes larger than table-scale – we plan to expand this to larger volumes and in-the-wild capture in the future.

Societal/Ethical Impact: Our dataset does not reveal any private information and presents limited means for misuse. However, future extensions of our work could contain private information that can be misused. Furthermore, the multimodal nature of the dataset presents challenges in reducing misuse and leaking of personal data that future research should explore.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [Yes]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments (e.g. for benchmarks)...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [Yes] MIT License
   (c) Did you include any new assets either in the supplemental material or as a URL? [No]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

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