Look Ma, No Hands!
Agent-Environment Factorization of Egocentric Videos
Supplementary Material

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S1 Video

The accompanying video (vidm.mp4) in MP4 (AAC, H.264) format provides a narrated overview of the method and shows example predictions visualizing our factorized representation on in-the-wild videos. The video was tested to play well in Google Chrome, VLC, and QuickTime.

S2 Code

Additionally, the supplementary material contains two files "model.py" and "config.yaml". These contain the code for our video inpainting diffusion model, and the parameters used in its instantiation respectively.

S3 VIDM Training Details

For an overview of the VIDM model architecture, see Main Paper Section 4. In each block, the CNN layers are implemented as residual blocks [9] with SiLU non-linearities [10] and each attention layer does self-attention across all token from all input images using 32-channel GroupNorm normalization. Following [14], upsampling and downsampling operations are both implemented using residual CNN blocks with either an internal nearest mode $2\times$ upsampling operation or internal $2\times$ downsampling via average pooling. An initial convolution brings the feature dimension to 256, which is raised to a maximum of 1024 at the center of the U-Net. At the highest spatial resolution of 64×64 the self-attention layer is omitted, as attention with 16384 ($= 64 \times 64 \times 4$) tokens is computationally intractable for our available hardware. The largest attention layer occurs at a spatial resolution of 32×32 across four images for a total of 4096 tokens.

We trained VIDM using target images from Ego4D [6] and VISOR [4] (see Main Paper Sec. 4). Since no evaluation was done on Ego4D, no Ego4D data was held out. For VISOR, all data from participants *P37, P35, P29, P05*, and *P07* was held-out from training. This held-out data from these participants was used for reconstruction quality evaluation (Main Paper Section 5.1) and object detection (Main Paper Section 5.2) experiments. Table S1 lists hyper-parameters. Figure S2 shows sample training batches.

S4 Downstream Task Experimental Details

S4.1 Detection

We used off-the-shelf Mask R-CNN R_101_FPN_3x from Detectron2 [8, 17] trained on the COCO dataset [11] for evaluation. We used overlapping classes between the VISOR [4] annotations and

Table S1: VIDM Model and Training Hyper-parameters.

Hyper-parameter	**Value**
Learning Rate	4.8×10^{-5}
Batch Size	48
Optimizer	Adam
Diffusion Steps (training)	1000
Latent image Size	64×64
Number of VQ Embedding Tokens	8192
VQ Embedding Dimension	3
Diffusion Steps (inference)	200
Attention Heads	8

COCO for evaluation. These were: *apple, banana, bottle, bowl, broccoli, cake, carrot, chair, cup, fork, knife, microwave, oven, pizza, refrigerator, sandwich, scissors, sink, spoon, toaster*.

S4.2 Affordance Prediction

Dataset: We experiment on EPIC-ROI and GAO tasks from Goyal *et al.* [5]. EPIC-ROI uses the EPIC-KITCHENS dataset [3] and GAO uses YCB-Affordance [2] dataset. We consider a low data regime in our work and sample $1K$ images from these datasets to train the different models. For EPIC-ROI, we sample images with a probability inversely proportional to the length of the video. For GAO, we sample randomly. We use the same evaluation setting from [5].

Model: We use the same architecture from ACP [5] and replace the EPIC-ROI input images with images produced by our inpainting model (with hands removed) to incorporate our factorized representation. While ACP [5] masks out a patch at the bottom center of the image to hide the hand, we do not need any mask (neither for training nor for testing) since the hands have been removed via inpainting. The input is processed by ResNet-50 followed by different decoders for EPIC-ROI and GAO tasks.

Training: We train separate models for EPIC-ROI and GAO using the loss function and hyperparameters from ACP [5]. While it is possible to train a single model in multitask manner, we observe that the two tasks are not complementary to each other. We train using 3 seeds for each task and report the mean and standard deviation in the metrics.

S4.3 3D Reconstruction of Hand-held Objects

Dataset: We use ObMan [7] dataset which consists of $2.5K$ synthetic objects from ShapeNet [1]. We use the train and test splits provided by Ye *et al.* [18]. We divide the train split into train and val set. The train set consists of $134K$, val set $7K$ and test set $6.2K$ images. The dataset provides 3D CAD models for each object, which we use for training hand-held object reconstruction model from Ye *et al.* [18].

Model: We use the architecture from Ye *et al.* [18]. It uses FrankMocap [16] to extract hand articulation features from a single image using MANO [15] hand parameterization. These hand features are used as conditioning to a DeepSDF [12] model which predicts the object shape using implicit representation. This model also takes in pixel-aligned features and global image features along with hand features. To incorporate our factorized representation, we also extract global image features and pixel-aligned features from ObMan images showing only objects (with hands removed). These features are concatenated with the features from the input ObMan images and fed as input to the DeepSDF [12] decoder.

Training: Following [18], we use a normalized hand coordinate frame for sampling points and predicting SDFs. We sample 8192 points in $[-1, 1]^3$ for training, out of which half of them lie inside and the rest lie outside the object. At test time, 64^3 points are sampled uniformly in $[-1, 1]^3$. We

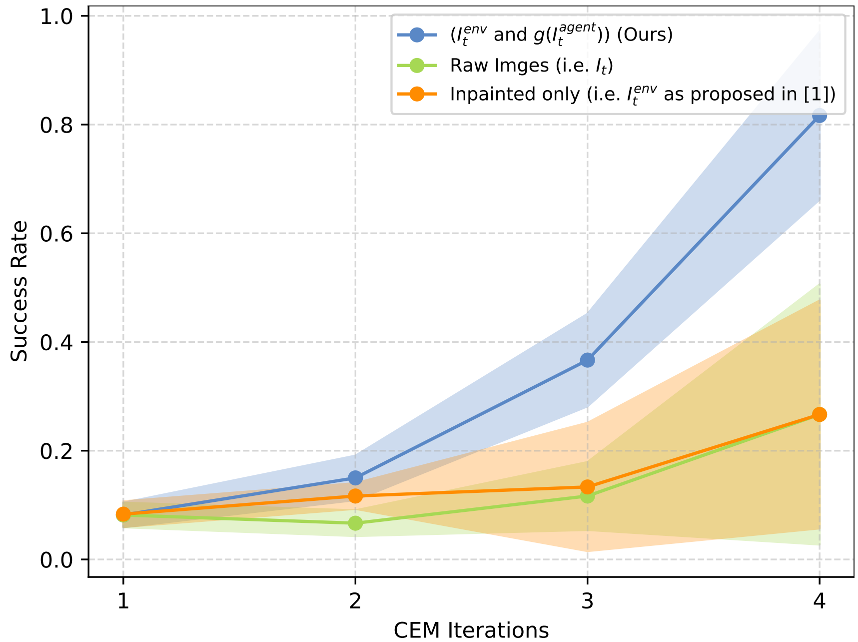


Figure S1: Success rate as a function of CEM iterations for the real-world experiment described in Main Paper Section 5.6. We report the mean and standard deviation across 3 runs for each method.

train the model in a supervised manner using 3D ground truth from ObMan [7] for 200 epochs with a learning rate of $1e-5$. Other hyper-parameters are used directly from [18].

S4.4 Error Bars for Real-World Policy Learning using Learned Rewards

In Figure S1, we report error bars for the real-world experiment (Main Paper Section 5.6) across additional runs. Across 3 runs for each method, we see that our method clearly performs the best (final mean success rate of 82% vs 27% for both baselines).

S5 Visualizations

In Figure S2, we include a visualization of a training batch for our method, showcasing supervision and generated masks. In Figure S3, we include additional visualizations of the predictions made by our method and baselines.

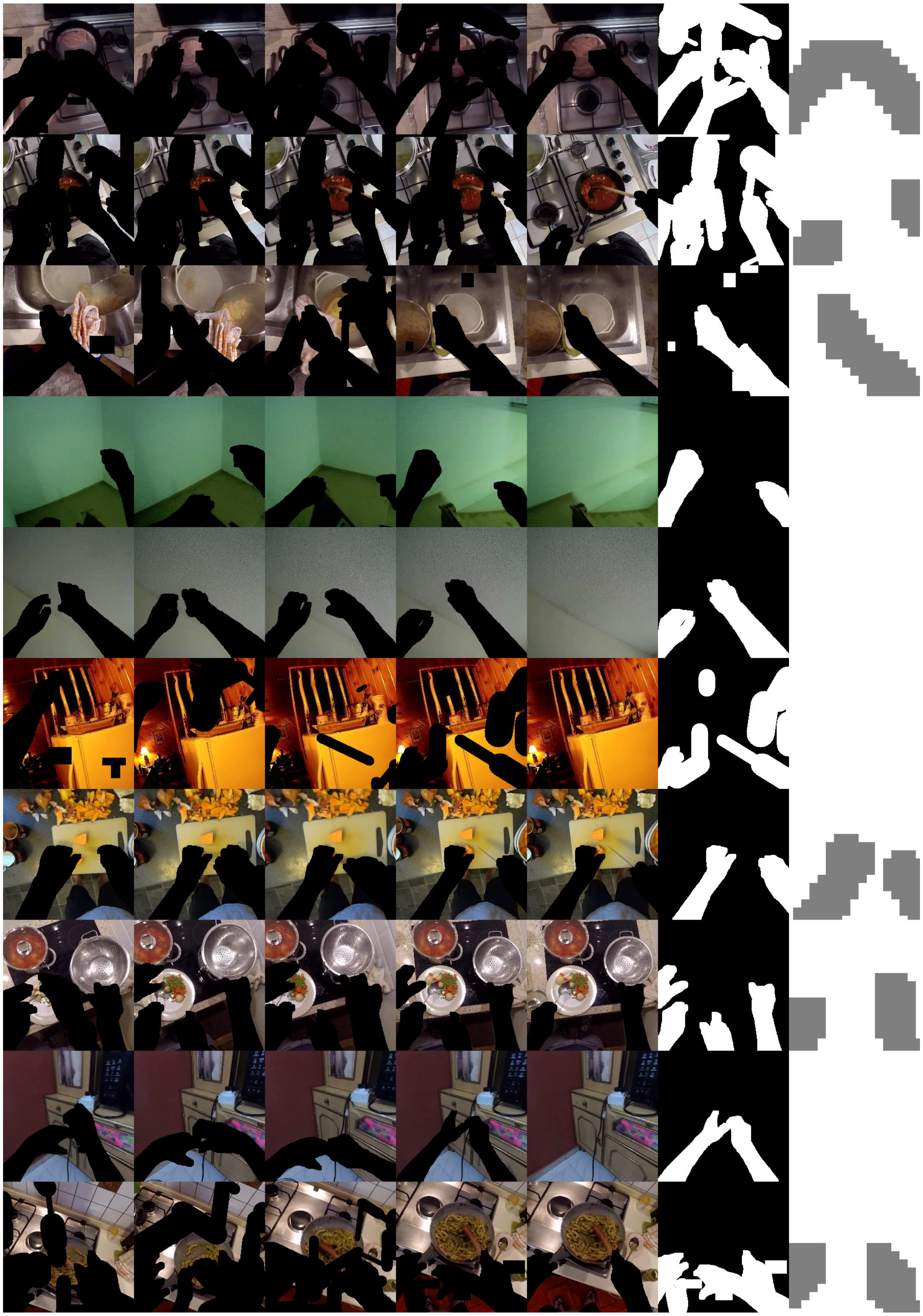
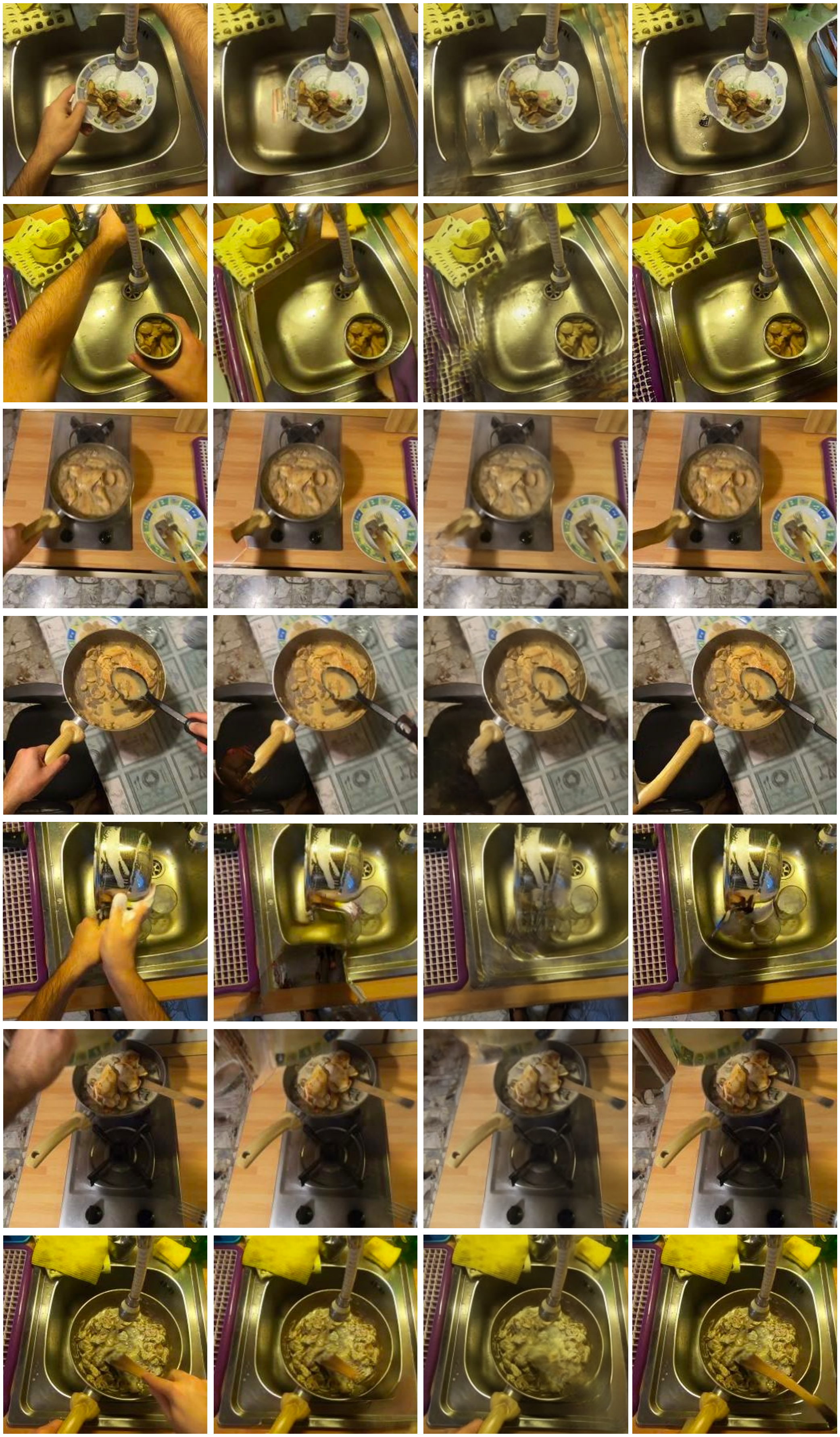


Figure S2: An example batch for training VIDM. Columns 1-4: Input images to the network. Column 5: target image for reconstruction. Column 6: Masked regions on the target image. Column 7: Pixels with loss propagated (white pixels have loss, gray pixels have no loss). Note that hands that are masked in the target image (column 5) have no loss on them. See Main Paper Section 4 for details.



a) Original Image b) LatentDiffusion FT [14] c) DLFormer [13] d) VIDM (Ours)

Figure S3: Additional visualizations of predictions from our method and baselines.

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