ObPOSE: Leveraging Canonical Pose for Object-Centric Scene Inference in 3D

Abstract

We present ObPOSE, an unsupervised object-centric generative model that learns to segment 3D objects from RGB-D video in an unsupervised manner. Inspired by prior art in 2D representation learning, ObPOSE considers a factorised latent space, separately encoding object-wise location (where) and appearance (what) information. In particular, ObPOSE leverages an object’s canonical pose, defined via a minimum volume principle, as a novel inductive bias for learning the where component. To achieve this, we propose an efficient, voxelised approximation approach to recover the object shape directly from a neural radiance field (NeRF). As a consequence, ObPOSE models scenes as compositions of NeRFs representing individual objects. When evaluated on the YCB dataset for unsupervised scene segmentation, ObPOSE outperforms the current state-of-the-art in 3D scene inference (ObSuRF) by a significant margin in terms of segmentation quality for both video inputs as well as for multi-view static scenes. In addition, the design choices made in the ObPOSE encoder are validated with relevant ablations.

1 Introduction

In recent years, object-centric representations have emerged as a paradigm shift in machine perception. Intuitively, inference or prediction tasks in down-stream applications are significantly simplified by reducing the dimensionality of the hypothesis space from raw perceptual inputs, such as pixels or point-clouds, to something more akin to a traditional state-space representation. While reasoning over objects rather than pixels has long been the aspiration of machine vision research, it is the ability to learn such a representation in an unsupervised, generative way that unlocks the use of large-scale, unlabelled data for this purpose. As a consequence, research into object-centric generative models (OCGMs) is rapidly gathering pace.

Central to the success of an OCGM are the inductive biases used to encourage the decomposition of a scene into its constituent components. With the field still largely in its infancy, much of the work to date has confined itself to 2D scene observations to achieve both scene inference [e.g. 1, 2, 3, 4, 5, 6, 7] and, in some cases, generation [e.g. 6, 7]. In contrast, unsupervised methods for object-centric scene decomposition operating directly on 3D inputs remain comparatively unexplored [8, 9] – despite the benefits due to the added information contained in the input. As a case in point, Stelzner et al. [9] recently established that access to 3D information significantly speeds up learning. Another benefit is that, for the parts of an object visible to a 3D sensor, object shape is readily accessible and does not have to be inferred either from a single view [e.g. 10, 11] or from multiple views [e.g. 12, 13]. Here we conjecture that object shape can serve as a highly informative inductive bias for object-centric learning. Irregular shape can be used to discover an object’s pose and pose can help to identify and locate objects in space.

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We present OBPOSE, an unsupervised OCGM that takes RGB-D video as input and learns to segment the underlying scene into its constituent 3D objects and a background. Inspired by prior art in 2D settings [1, 14, 15, 16, 17, 18], OBPOSE factorises its latent embedding into a component capturing an object’s location and appearance (where and what components, respectively). This factorisation provides a strong inductive bias, helping the model to disentangle its input into meaningful concepts for later use.

A key contribution of OBPOSE is the introduction of a novel inductive bias, canonical pose, which leverages observed and imagined (in occlusions) object shape to inform the learning of the where component in 3D. Taking inspiration from the use of canonical pose in the pose estimation literature [e.g. 19], the intuition for OCGMs is that observed differences in object pose should be invariant in the latent space. We propose to infer canonical pose without supervision, using a minimum volume principle defined using the tightest bounding box that constrains an object. In addition, we propose a voxelised approximation approach that recovers an object’s shape, in a computationally tractable way from a neural radiance field (NeRF) [20]. Although the recovery of an object’s shape from a NeRF can be prohibitively expensive, our approach allows this to be integrated efficiently into the OBPOSE training loop.

In a series of experiments, OBPOSE outperforms ObSuRF [9], the current state-of-the-art in 3D scene inference, by significant margins. Evaluations are performed on the YCB dataset for unsupervised scene segmentation [21], using both RGB-D video and multi-view static scenes. Ablations on the OBPOSE encoder validate the design decisions that distinguish its use of attention mechanisms from two alternatives, represented by Slot Attention [5] and GENESIS-v2 [7]. The key contributions of this paper are: (1) a new state-of-the-art unsupervised scene segmentation model for 3D, OBPOSE, together with insights into its design decisions; (2) a novel inductive bias for 3D OCGMs, canonical pose; and (3) a general method for fast shape evaluation that enables efficient training.

2 Methods

OBPOSE takes RGB-D videos as input and learns to segment scenes into a set of foreground objects, with a single background component. The location and orientation of objects (i.e. pose) can be estimated based on the objects’ respective shapes, using NeRFs [20]. Each NeRF models an implicit function representation of the 3D geometry and the textures of a scene component. OBPOSE performs
three steps for each video frame observed: First, an instance colouring stick-breaking process (IC-SBP) step is performed which clusters pointwise embeddings, encoded from a KPConv [22] backbone, into soft attention masks of objects. Second, a where-inference step is taken that predicts the object locations and orientations according to the object-wise attention masks from the IC-SBP. Finally, a what-inference step encodes the appearance and shape information conditioned on the object poses and then decodes these into NeRFs. These are then composed together with the background component to reconstruct the original scene. A schematic overview of the OBPOSE architecture is provided in Figure 2.

Figure 2: Model architecture. Given an input RGB-D image \(x\), the KPConv backbone extracts point embeddings \(\xi\) and a background component \(z_{bg}\). The point embeddings are clustered by the IC-SBP into soft attention masks, \(m_1 \ldots m_K\), for each object slot. Given these object masks, a where module infers the location of each object encoded by \(z_{\text{where}}\). Conditioned on object poses, which are recovered via the minimum volume principle, the what latents, \(z_{\text{what}}\), are encoded and then decoded into object NeRFs. Object NeRFs are finally composed with the background component to reconstruct the observed scene.

2.1 Encoder

The input observation \(x_t\) is a RGB-D image of height \(H\) and width \(W\) for each time-step \(t \in \{1 \ldots T\}\). RGB-D depth images are converted into the point clouds \(p_t\) using the known camera parameters (extrinsic and intrinsic). The point clouds \(p_t\) and the RGB channels of \(x_t\) are then concatenated and encoded into a point embedding \(\xi_{H_1 \times W_1 \times D_i}\). This is achieved using a U-Net-like backbone module [23] consisting of several KPConv layers [22]. A KPConv layer is an extension of a 2D convolutional neural network (CNN) layer for point clouds, which preserves the translation invariance properties of CNNs. For computational efficiency, output embeddings are upsampled to the resolution of the first downsampled embedding using trilinear interpolation. An aggregation layer is required to summarise the global information for encoding the background information into the latent representation \(z_{bg}\). For classification tasks, average pooling was adopted for aggregation [22]. However, the pooling is not suitable for capturing the location information of the input features. Instead, we use a KPConv-aggregate layer to aggregate the output features, initialising a convolutional kernel at the coordinate centre. In this way, global spatial information is preserved and encoded in the relative distances between the output features and the kernel points. Following prior work [7], we additionally build two heads upon the output embedding \(\xi\), with one predicting the colour embedding \(\xi_{H_1 \times W_1 \times D_c}\) for the IC-SBP, and the other predicting the feature embedding \(\xi_{H_1 \times W_1 \times D_f}\) for other encoding tasks.

2.1.1 Instance Colouring Stick-Breaking Process for Video

An instance colouring stick-breaking process (IC-SBP) takes point embeddings \(\xi_{H_1 \times W_1 \times D_i}\) as inputs and outputs \(K\) predicted soft attention masks \(m_k \in [0, 1]^{H_1 \times W_1}\). The stick-breaking process [2] guarantees that the masks are normalised:

\[
m_1 = \alpha_1, \quad m_k = s_{k-1} \odot \alpha_k, \quad m_K = s_K,
\]

where the scope \(s_k \in [0, 1]^{H_1 \times W_1}\) tracks which pixels have not yet been explained. \(s_k\) is initialised and updated as follows:

\[
s_0 = \mathbb{1}^{H_1 \times W_1}, \quad s_k = s_{k-1} \odot (1 - \alpha_k)
\]
The alpha mask $\alpha_k$ is computed as the distance between a cluster seed $\zeta_{i,j}$ and all individual point embeddings according to a kernel $\psi$. Readers are referred to the relevant literature [7] for details on kernel selection; our implementation uses Gaussian kernels. The IC-SBP prevents the model from learning a fixed order of decomposition. It achieves this by selecting the cluster seed at the spatial location $(i, j)$ according to the argmax of a score mask $s_k = s_k \odot u$ with $u$ being a score map sampled from a uniform distribution $U(0, 1)^{|H| \times |W|}$. The score map $u$ ensures the stochastic ordering of the mask $m_k$.

Although the IC-SBP is by default agnostic with respect to the slots, there are nonetheless special components in scene segmentation such as the background. We model slots like these that contain special components by passing the pixel embeddings $e_c^{H_i \times W_i \times D_c}$ through a multilayer perceptron (MLP) $\rho$ to compute a pre-scope $s^p$:

$$s^p = \text{softmax}(\rho(\zeta) \in \mathbb{R}^{H_i \times W_i \times K'})$$

Here $K' - 1$ is the number of special slots. By convention we take the last channel of $s^p$ to be the scope $s_0$ in the IC-SBP. In the present study, we set $K' = 2$ for only modelling the background. A termination mechanism is implemented by sampling from the remaining scope $s_k$ before computing the alpha mask $\alpha_k$ at each step $k$. Each point in the scope $s_k$ is treated as an independent Bernoulli distribution with the probabilities being the scope value and perform point-wise sampling. The current slot is set to the idle state when all sampled values are zero, which indicates that the whole observation has been explained by previous slots. This contrasts with prior work where a termination condition is proposed to indicate when the IC-SBP should stop [7].

For the video input, we extend the original IC-SBP to include an additional propagation step. The cluster seed $\zeta_{i,j}$ can be used as an ID for each slot throughout the video. The cluster seed sampled at $t = 1$ is stored and used to compute the alpha masks for frames of $t \geq 2$. The idle slots detected at $t = 1$ will remain in idle states during propagation. To ensure the normalisation of the masks $m_k$, the SBP operation of IC-SBP takes the remaining scope $s_K$ as the last component mask $m_K$. This does not have an associated seed for propagation. We run one more step of the SBP for the last component and flag the remaining scope $s_K$ as unused. Concretely, we add an additional penalty loss to encourage the final remaining scope $s_K$ to be zero everywhere, thereby motivating the model to explain the whole observation using only the previous slots.

### 2.1.2 Canonical Pose Conditioned Encoding

Pose-invariance is a valuable property in a latent space focused on objects. To evaluate the pose, we note that the point cloud can be viewed as a discrete sampling from the object surface and thus preserves the shape information of the objects. A canonical pose can be defined given that $P_{t,k} = \{ \mathbf{p}_j | j \in \{1, ..., N_k\} \}$ is a set of points that approximates the 3D shape of object $k$ at time step $t$. Intuitively, the location of the object $T_{t,k}$ can be initialised at the centre of mass of $P_{t,k}$:

$$T_{t,k} = \frac{1}{N_k} \sum_{j \in \{1, ..., N_k\}} \mathbf{p}_j$$

with $N_k$ being the number of points of object $k$. For the orientation of the object, which can be represented by a rotation matrix $\mathbf{R}_{t,k} \in \text{SO}(3)$, we propose the following minimum volume principle to define a unique shape-based object orientation: given a set of points, we set the canonical orientation of the object represented by those points to the orientation of the tightest bounding box that contains those points. Concretely, we find this bounding box by first transforming the points under several selection rotation matrices $\mathbf{R} \in \text{SO}(3)$ and then computing the volume of the axis-aligned bounding boxes (AABBs) that contain these points. Selection rotation matrices are generated as equivolumetric grids in the SO(3) manifold [24, 25]. This method is based on the HEALPix method of generating equal area grids on the 2-sphere [26]. Due to the symmetry property of the bounding boxes, the smallest bounding box can have multiple solutions, e.g., swapping the x-axis and the y-axis of the coordinates of the bounding box will result in another bounding box that has the same volume. Therefore, we select all the bounding boxes whose volumes are in the range $[V_{\text{min}}, (1 + \beta) V_{\text{min}}]$ to account for this issue, where $V_{\text{min}}$ is the minimum volume of all the AABBs and $\beta$ is a small tolerance factor. We pick the AABB whose orientation is closest to the world coordinates and whose orientation is represented by the identity matrix $\mathbf{I} \in \mathbb{R}^{3 \times 3}$. The distance $d_{\text{SO}(3)}$ is measured by the
geodesic distance on the SO(3) manifold:

\[ d_{SO(3)} = \arccos \left( \frac{\text{tr}(R_{t,k}) - 1}{2} \right) \]  

(5)

The points \( p_j \) are then transformed to their canonical coordinates given a pair of pose parameters \( \{ T, R \} \) as follows:

\[ k \left( p_j, R, T \right) = \frac{2}{s} (R)^{-1} (p_j - T) \]  

(6)

The bounding box size \( s \in \mathbb{R} \) is initialised to a sufficiently large number for all objects. All points that are out of the bounding box are discarded so that the spatial coordinate of each point is in the range of \([-1, 1]\).

For each object slot at time step \( t \), we find its associated point cloud \( P_{t,k} \) by computing the argmax over the attention masks \( m_{t,k} \) predicted from the IC-SBP. The point features \( \zeta_{f,t} \) at time step \( t \) are also masked by the attention masks, i.e. \( \zeta_{t,k} = \zeta_{f,t} \odot \text{detach}(m_{t,k}) \). The object location \( T_{t,k} \) estimated from the observed points \( P_{t,k} \) is, however, biased toward object surface as the object is only partially observed. We thus use a `where` module that takes \( P_{t,k} \) and \( \zeta_{t,k} \) as input and predicts a \( \Delta T_{t,k} \) to correct the bias. To learn a relative translation we first transform \( P_{t,k} \) using the pose parameters \( \{ T_{t,k}, I \} \) as in eq. (6). Concretely, the `where` module is an encoder that consists of several KPConv layers and a KPConv-aggregate layer as the final output layer. The encoded embedding is then fed to a recurrent neural network (RNN) with its hidden states later being decoded into the mean and standard deviation of the posterior distribution \( q(z_{t,k}^{\text{where}} | x_{\leq t}) \) parameterised as a Gaussian. The \( z_{t,k}^{\text{where}} \) is decoded to the \( \Delta T_{t,k} \) through an MLP \( f_{\text{where}} \) such that:

\[ \Delta T_{t,k} = T_{\text{max}} \tanh(f_{\text{where}}(z_{t,k}^{\text{where}})) \]  

(7)

with \( T_{\text{max}} \in \mathbb{R} \) being the maximum delta translation. Given the updated object location \( \hat{T}_{t,k} = T_{t,k} + \Delta T_{t,k} \), we encode the shape and the appearance of the object from the observations transformed in the canonical pose \( \hat{\{ \hat{T}_{t,k}, \hat{R}_{t,k} \}} \). Similar to the `where` module, the posterior distribution \( q(z_{t,k}^{\text{what}} | x_{\leq t}, x_{\geq t}) \) is also parameterised by a KPConv encoder appended by an RNN. If the point number \( N_k \) is small, we instead initialise the canonical pose \( \hat{T}_{t,k}, \hat{R}_{t,k} \) with the object location from the last time step, i.e. \( \{ \hat{T}_{t-1,k}, I \} \) during the propagation.

We use two RNN networks to model the prior distributions \( p(z_{t,k}^{\text{where}} | x_{\leq t,k}) \) and \( p(z_{t,k}^{\text{what}} | x_{\geq t,k}) \), whose hidden states are decoded by an MLP to the mean and standard deviation. The prior distribution at \( t = 0 \) are Gaussian distributions of zero mean for both the \( z^{\text{where}} \) and the \( z^{\text{what}} \).

### 2.2 Decoder

To explicitly model the 3D geometry of scenes, we represent each object and the background as a Neural Radiance Field (NeRF) [20]. Each NeRF is a function parameterised by an MLP that maps the world coordinates \( p \) and the viewing direction \( d \) to a color value \( c \) and a density value \( \sigma \). One limitation is that a given NeRF can only represent a single scene and cannot condition on the latent encoding. The approach has therefore been extended [27, 28] to learn the mapping \( f : (p, d, z) \rightarrow (c, \sigma) \). This introduces a mapping from the latent encoding \( z \) to modifications to the hidden layer outputs of the NeRF MLP. To compose the individual NeRFS into a single scene function, previous approaches [9, 28] combine the density values by a summation operation, i.e. \( \sigma = \sum_{k=1}^{K} \sigma_k \). This way of composing NeRFS is equal to a superposition of independent Poisson point processes [9]. The scene colour can then be computed as a weighted mean \( c = \frac{1}{\sigma} \sum_{k=1}^{K} \sigma_k c_k \). We know that a voxel should not be occupied by multiple objects. To account for this property, [9] proposes an auxiliary loss to penalize the difference between the sum of the density values and the maximum density values of all components, as simply composing NeRFSs with a summation does not suffice. This auxiliary loss, however, requires a warm-up training strategy and introduces additional hyper-parameters for different datasets. We thus propose to model the scene function as:

\[ \sigma = \sigma_{\text{max}} \tanh \left( \sum_{k} \text{softplus} (\sigma_k) \right), \hat{\sigma}_k = \sigma \text{softmax} (\sigma_k) \]  

(8)

In our case, \( \sigma_k \) can be interpreted as the logits of the probability, indicating whether this voxel is occupied or not, and \( \hat{\sigma}_k \) is the normalised density with a range of \([0, \sigma_{\text{max}}]\). For the colours, we can
compute the weighted mean: \( c = \frac{1}{\sigma_{\text{max}}} \sum_{k=1}^{K} \hat{\sigma}_k c_k \). We upper bound the density by \( \sigma_{\text{max}} \in \mathbb{R} \) and model the probability of whether the voxel has been occupied through a tanh. The softplus function ensures that no component can contribute negative occupancy. We use the softmax function to account for the fact that the objects should not overlap, without needing to introduce extra hyper-parameters. To estimate the shape of the objects reconstructed from the NeRFs, we would like a fast approximation approach, as the full evaluation of the volumetric rendering is computationally expensive. Inspired by prior work [29], we divide each object bounding box into \( S \) sparse voxels along each dimension. The occupancy at these voxel centres \( p_{\vec{v}} \) can then be evaluated by \( \sigma_{\vec{v}} = \tanh(\hat{\sigma}_k p_{\vec{v}} - z_k) \). We denote the voxels as occupied if \( \sigma_{\vec{v}} > \sigma_T \), with the \( \sigma_T \) being a threshold. Given the set of the occupied voxels and their centre positions \( p_{\vec{v}} \), we can recover the canonical object centre \( T_{\text{shape}, t} \) and the object orientation \( R_{\text{shape}, t} \) as discussed in 2.1.2.

3 Training

Training a NeRF with known depth requires relatively few evaluations. Stelzner et al. [9], for example, propose to use only two evaluations of the NeRF for each training iteration, i.e. one evaluation at the surface and one evaluation at points between the camera and the surface. To avoid learning an extremely thin surface, the points sampled at the surface are sampled between the depth range \([d_{\text{surface}}, d_{\text{surface}} + \delta]\), with the \( \delta \) denoting the surface thickness. The observation loss can be divided into two terms, i.e. a texture loss term:

\[
L_{\text{colour}} = -\log(\sum_{k=1}^{K} N(c_k, \sigma_{\text{std}}) \circ \hat{\sigma}_{k}^{\text{surface}} / \sigma_{\text{max}})
\]  

with \( \sigma_{\text{std}} \) denoting a fixed standard deviation, and a depth loss term [9]:

\[
L_{\text{depth}} = -\log(\sigma(p_{\text{surface}})) + \sigma(p_{\text{air}}) / \rho_{\text{air}}
\]  

where \( \rho_{\text{air}} \) is a probability density of the point \( p_{\text{air}} \) being sampled. The latent embedding is regularized using the KL term:

\[
L_{\text{KL}} = KL(q_{\phi}(z_t | z_{\leq t}, x_{\leq t}) || p_{\theta}(z_t | z_{\leq t}))
\]  

An L2 loss is used to supervise the where module:

\[
L_{\text{where}} = \sum_k (\hat{T}_{t,k} - T_{t,k}^{\text{shape}})^2
\]  

For the attention mask of the IC-SBP, the learning of the attention masks is supervised via:

\[
L_{\text{att}} = -((\log(\sum_{k=1}^{K} m_k \circ (N(c_k, \sigma_{\text{std}}) \circ \hat{\sigma}_{k}^{\text{surface}} / \sigma_{\text{max}}))) + \log(\sum_{k=1}^{K} m_k \circ \hat{\sigma}_{k}^{\text{surface}} / \sigma_{\text{max}}))
\]  

In the end, we penalise the remaining scope \( s_K \) by introducing the remaining scope loss:

\[
L_{\text{scope}} = \sum_{i=1}^{H_1} \sum_{j=1}^{W_1} s_{K,i,j}
\]  

Taken together, these losses lead to the overall loss:

\[
L = L_{\text{colour}} + L_{\text{depth}} + L_{\text{KL}} + L_{\text{where}} + L_{\text{att}} + L_{\text{scope}}
\]  

For the training, we use the Adam optimizer with a fixed learning rate of \( 4e^{-4} \) and without any learning rate warm-up or decay strategy.

4 Experiments

To evaluate OBPOSE’s performance on unsupervised segmentation tasks of 3D scenes and to demonstrate its ability to estimate 6D poses of objects, we conduct experiments on two YCB object datasets [21]. One is a video dataset of RGB-D images captured from a fixed front view and another is a dataset of static images captured from three different points of view. The three views are obtained by
rotating the camera by $120^\circ/240^\circ$ around the z-axis of the world frame. All images are shuffled so that ground-truth pairing information is not used for training. In each dataset, two to four randomly selected objects are spawned on the table. The metrics used for evaluation are described below. Performance is compared against the recent baseline of ObSuRF [9], which, to the best of our knowledge, is the only unsupervised scene segmentation model that operates on RGB-D images of 3D scenes. To validate our model design decisions, we also compare performance using different attention mechanisms on the encoder side, i.e. slot attention [5] and IC-SBP [7] with an object encoder that does not model object pose. In addition, we also compare two ablations of the OBPOSE encoder, i.e. one conditioned only on the locations of the objects and one conditioned on the full 6D poses.

4.1 Metrics
Segmentation quality is quantified using the Adjusted Rand Index (ARI) [30, 31] and Mean Segmentation Covering (MSC) as metrics. In contrast to mean Intersection over Union (mIoU), ARI measures the clustering similarity between the predicted segmentation masks and the ground-truth segmentation masks in a permutation-invariant fashion. This is suitable for unsupervised segmentation approaches as there are no fixed associations between slots and objects. We evaluate segmentation accuracy on foreground objects using the foreground-only ARI and MSC (denoted ARI-FG and MSC-FG, respectively), and on the background using mIoU. All metrics are normalised with possible values ranging between 0 and 1, where a score of 1 indicates perfect segmentation.

4.2 Unsupervised 3D Object Segmentation
Qualitative results on the YCB video dataset are depicted in Figure 3. Quantitative segmentation results are additionally summarised in Table 1. Taking these in turn, we first observe that the ObSuRF baseline fails to segment the scenes properly using the default setting for 3D data from the open-sourced code. This might be attributed to the weight of a overlap loss used in ObSuRF, to discourage the objects from overlapping. In Stelzner et al. [9] the same failure mode is reported and thus a warm-up of the weight is carefully chosen for training. In OBPOSE, we instead use the softmax function in Equation (8). This provides an inductive bias without hyper-parameters, alleviating the computationally expensive hyper-parameter searching process. Interestingly, using the full 6D pose including the orientation and the location of the objects does not strongly affect the
Table 1: Mean and standard deviation of the segmentation metrics on the YCB video dataset and the YCB static dataset from three random seeds. The results are rounded to two decimal places.

|                      | YCB Video |          |          | YCB Static |          |          |
|----------------------|-----------|----------|----------|------------|----------|----------|
|                      | mIoU-BG   | ARI-FG   | MSC-FG   | mIoU-BG   | ARI-FG   | MSC-FG   |
| OBPOSE               | 0.96 ± 0.00 | 0.00 ± 0.00 | 0.00 ± 0.00 | 0.92 ± 0.00 | 0.00 ± 0.00 | 0.00 ± 0.00 |
| SLOT ATT. *          | 0.98 ± 0.02 | 0.13 ± 0.05 | 0.19 ± 0.02 | 1.00 ± 0.00 | 0.80 ± 0.01 | 0.84 ± 0.00 |
| IC-SBP               | 0.96 ± 0.05 | 0.87 ± 0.02 | 0.90 ± 0.02 | 0.97 ± 0.03 | 0.83 ± 0.09 | 0.80 ± 0.15 |
| OBPOSE (ours)        | 1.00 ± 0.00 | 0.96 ± 0.00 | 0.97 ± 0.00 | 0.99 ± 0.00 | 0.89 ± 0.01 | 0.87 ± 0.03 |
| OBPOSE + ROT. (ours) | 1.00 ± 0.00 | 0.96 ± 0.00 | 0.97 ± 0.00 | 0.98 ± 0.00 | 0.88 ± 0.01 | 0.84 ± 0.03 |

* The SLOT ATT results are computed with one failed random seed being excluded for the YCB static dataset.

Figure 4: Visualisation of the voxelised shape reconstruction for each object, and for the recovered bounding boxes estimated from the reconstructed object shape, as viewed from the back side of the scene. The centres of the occupied voxels of each object are shown in distinct colours. The object-centric NeRFs learn to interpolate the inner body of the objects with high density predictions.

segmentation performance compared to using only the object positions as a way to condition the encoding. This suggests that for object segmentation tasks, the object location itself already provides a strong inductive bias for successful decomposition. Similar results are observed elsewhere in the literature [32], where simple ground-truth position information for objects is used in the first video frame, allowing the model to perform scene segmentation of 2D video data in a weakly supervised fashion. In our approach, we explicitly leverage the 3D reconstruction of the objects whose shape is estimated by the proposed voxelised shape approximation approach. This allows the model to infer the canonical poses of objects in a computationally efficient way without using any ground-truth labels. OBPOSE also achieves lower variation on metrics for both datasets, suggesting more stable training compared to the original IC-SBP.

4.3 Unsupervised 6D Pose Estimation and Shape Completion with Object-centric NeRFs

The unsupervised 6D pose estimation results are illustrated in Figure 4. In our model, the locations of objects are predicted directly as the outputs of the where module, whereas the orientations are estimated by the proposed minimum volume principle (Section 2.1.2). Evaluating the locations and orientations of objects requires a set of sparse points in 3D that approximate the objects’ shapes. To achieve this, we could either mask out the observed point cloud with the attention masks predicted from the IC-SBP, or we could use the voxelised shape approximation computed in the decoder step as the shape approximation. The former method provides the model with a stable shape signal, as it
relates directly to the ground-truth observations; this method is used in the full 6D pose conditioned encoding ablation for robust training. On the other hand, the latter method reconstructs the full 3D shape of the objects including the unobserved parts, and is thus a more accurate approximation of the object shapes. We therefore use the voxelised shape approximation in the evaluation phase as visualised in Figure 4. We find that the object NeRFs learn to interpolate the inner body of the objects with high occupancy predictions, even though the training signals are preempted near the object surface due to the volume rendering. This property of NeRFs allows us to estimate accurate centres of mass and object orientations. We further observe that on the YCB video data, where all observations are captured from a single front view, the object NeRFs can still reconstruct the unobserved back side of the objects. In most NeRF applications, a multiple-view setting with known camera parameters is usually assumed. However, our work indicates the possibility of applying NeRFs in scenes observed from a single view, where objects are moving but the camera is fixed. Such a setting has potential for applications such as robot grasping tasks, where a camera is commonly positioned in front of a table.

5 Related Work

OBPOSE builds upon prior OCGM work on unsupervised segmentation in both 2D and 3D. It is also related conceptually to previous work on canonical pose, in supervised and unsupervised settings.

Most OCGMs for 2D scene segmentation are formulated as variational autoencoders (VAEs) [33, 34], where different likelihood models serve to explain observations. One set of VAE-OCGMs use bounding boxes, derived from spatial transformer networks (STNs) to represent (glimpse) individual objects [1, 35, 14, 15, 16, 17]. Another set represents objects via unsupervised instance segmentation, using pixel-wise mixture models [2, 6, 36, 3, 4, 37, 38, 39, 3]. This latter set relaxes the spatial-consistency requirements imposed by bounding boxes [40], permitting more flexible modelling of objects with complex shapes and textures. However, relaxing spatial consistency has the side-effect that performance can sometimes be biased by features such as the colour of the object [41], which has motivated the search for additional inductive biases. A promising candidate is temporal information. To this end, some works [39, 42, 32] operate on video data and model the correlations between objects explicitly using graph neural networks (GNNs) [43, 44] or Transformers [45].

With the advent of differentiable rendering techniques [10, 20], recent works have begun to model the observed scene directly in 3D [46, 28, 9, 12]. This leads to improved data-efficiency as the rendering process accounts for spatial relationships such as occlusions without the requirement of learning these effects from data. Work on unsupervised 3D scene segmentation has learned from multiple static images or RGB-D images of scenes, not previously from video.

The idea of a canonical pose, or reference pose for an object, has precedent in the context of 6D pose estimation, which aims to find the translation and rotation of an object with respect to some frame of reference. In the supervised setting, labels are defined with respect to a given canonical frame [19, 47, 48, 49, 50, 51]. Recently, it has been shown that pose between views of an object, or objects from a common category, can be inferred without labels. Such relative poses have been found for point clouds [52] and RGB-D images [53]. To the best of our knowledge, we are the first to propose a minimum volume approach for discovering canonical pose without supervision and to use canonical pose as an inductive bias.

6 Conclusion

We present OBPOSE, an object-centric generative model that is able to decompose 3D scenes into objects and background, with each object being represented as a NeRF. OBPOSE extends IC-SBP for video data and introduces canonical poses of objects as a powerful inductive bias for unsupervised segmentation. Learning object locations is facilitated by a number of recent developments: the implicit function representations of the 3D shapes and the fast voxelised shape approximation proposed in this paper. Our experimental results are validated on two established synthetic YCB objects datasets (static 3D and video). Given its empirical success, outperforming the prior state-of-the-art for static 3D scenes [9] and establishing a baseline for video, we plan to apply OBPOSE as a vision backbone for robot applications.
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Appendix

6.1 Minimum Volume Principle in Detail

The proposed approach for recovering the canonical pose for an object is described in Algorithm 1. A visualisation of how the estimated canonical pose evolves as the volume of the AABB that contains the object decreases is depicted in Figure 5. An advantage of the proposed minimum volume principle is that the recovered canonical pose will align one of its coordinate planes with the symmetry plane of the object if it exists.

![Image of chair in arbitrary pose and its canonical pose]

Figure 5: We demonstrate the point cloud of a chair (A) in arbitrary pose (B) and how its canonical pose is recovered using the minimum volume principle. The selection matrices $R^s$ are illustrated in (C) by rotating a point at $[1, 1, 1]$ with all the selection matrices. (D) and (E) depict how the estimated object orientation represented by a bounding box and the object viewed in its canonical pose evolve with respect to the volume of the AABB.

Algorithm 1: Minimum Volume Principle

Input: points $P \in \mathbb{R}^{N \times 3}$ representing the object, and selection rotation matrices $R^s \in \mathbb{R}^{N_s \times 3 \times 3}$.

Output: translation and rotation parameters $\{T, R\}$ that map $P$ to their canonical coordinates.

1. $\beta \leftarrow 0.01$ \hfill \text{\# Tolerance hyperparameter}
2. $\hat{P} = (R^s)^{\top}P$ \hfill \text{\# Transform points into coordinates with orientations $R^s$}
3. $V = \text{COMPUTE VOLUME}(\hat{P})$ \hfill \text{\# Compute volume of AABBs that contain $\hat{P}$}
4. $V_{\text{min}} = \min(V)$ \hfill \text{\# Find smallest volume}
5. $R^v = \{R_j^v[V_i \in [V_{\text{min}}, (1 + \beta)V_{\text{min}}]]\}$ \hfill \text{\# Select similar sized AABBs to minimum}
6. $d_{SO(3)} = \arccos\left(\frac{(R^v)^{\top} - 1}{2}\right)$ \hfill \text{\# Compute geodesic distance to the world frame}
7. $R = R_j$ with $j = \arg\min(d_{SO(3)})$ \hfill \text{\# Find AABB closest to the world frame}
8. $T = \frac{1}{N} \sum_{i \in \{1, \ldots, N\}} p_i$ with $p_i \in P$ \hfill \text{\# Compute centre of mass for points}

6.2 Training and Implementation Details

Training takes about 35 hours for the YCB video dataset and 20 hours for the YCB static dataset on a single NVIDIA Titan RTX GPU. The video model and the static model are trained for 100k and 100.5k iterations, each with a batch size of 2 and 8, respectively, selected according to the available GPU memory. The IC-SBP ablation has a batch size of 8 for the video experiments as it’s a static image-based approach. For ObSuRF, we train for 90k and 100.5k with a batch size of 32 for the video and static image data. Video length is 5 frames randomly cropped from the full video for training and we use the full video length (typically 15 frames or longer) for testing. The model is thus able to process videos that are much longer than the videos seen during training. The YCB video dataset...
The present work advances the state-of-the-art in unsupervised 3D-scene segmentation and interpretation. While ObPose is important for advancing research, its impact outside of the machine learning community is low as current methods can not yet deal effectively with real images. This highlights the current limitations of the proposed model. In the future, we will investigate how to build a model...

Table 2: Hyperparameters of ObPose.

| Parameter | Description                              | Value |
|-----------|------------------------------------------|-------|
| $\sigma_{\text{std}}$ | Standard deviation of colour dist. | 0.1   |
| $\sigma_{\text{max}}$ | Maximum density                      | 10    |
| $s$       | Bounding box size                        | 0.4   |
| $N_{\text{thresh}}$ | Number of points to use the pose of last time step | 10    |
| $T_{\text{max}}$ | Maximally allowed $\Delta T$ | 0.1   |
| $S$       | Number of sparse voxels along each dimension | 24    |
| $\delta$ | Noise added to depths $d_{\text{surface}}$ | 0.01  |
| $\beta$  | Tolerance factor to select minimum volume bounding box | 0.01  |
| $K$       | Number of slots for IC-SBP               | 4     |
| $d_z$     | Dimensionality of both $z^\text{where}$ and $z^\text{what}$ | 32    |

6.4 Segmentation Results on YCB Static

We illustrate additional segmentation results on YCB static dataset in fig. 6.

6.5 Limitations and Potential Societal Impact

The present work advances the state-of-the-art in unsupervised 3D-scene segmentation and interpretation. While ObPose is important for advancing research, its impact outside of the machine learning community is low as current methods can not yet deal effectively with real images. This highlights the current limitations of the proposed model. In the future, we will investigate how to build a model...
that can explain complex real-world observations including e.g. shadows. OBPOSE will then be ready for real-world robotics applications as a vision backbone.