Watch It Move: Unsupervised Discovery of 3D Joints for Re-Posing of Articulated Objects

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(a) Multi-View Video (b) RGB and Parts Reconstruction (c) Re-Posing (d) Other Categories

Figure 1: Animated figure (view in Adobe Reader and click on panes (b), (c), and (d)). Our method learns to render novel views of an articulated, moving object by “watching” it move in a multi-view video sequence and associated foreground masks, as shown in the animation in (b). Simultaneously, it discovers the object’s parts and joints with no additional supervision. The learned structure can be used to explicitly re-pose the object, by roto-translating each part around its joint. In panes (c) and (d) we re-pose objects from different categories to configurations never seen in training, an operation only possible thanks to the structure we discover from the input videos.

Abstract

Rendering articulated objects while controlling their poses is critical to applications such as virtual reality or animation for movies. Manipulating the pose of an object, however, requires the understanding of its underlying structure, that is, its joints and how they interact with each other. Unfortunately, assuming the structure to be known, as existing methods do, precludes the ability to work on new object categories. We propose to learn both the appearance and the structure of previously unseen articulated objects by observing them move from multiple views, with no additional supervision, such as joints annotations, or information about the structure. Our insight is that adjacent parts that move relative to each other must be connected by a joint. To leverage this observation, we model the object parts in 3D as ellipsoids, which allows us to identify joints. We combine this explicit representation with an implicit one that compensates for the approximation introduced. We show that our method works for different structures, from quadrupeds, to single-arm robots, to humans.

1. Introduction

Using images to infer both the appearance and the functional structure of generic, real-world objects is a fundamental goal of computer vision. From a practical standpoint, it would allow to render and manipulate physical objects in the metaverse. But its appeal goes further, as it requires pushing the boundaries of our ability to learn from data with no direct supervision.

Our community made dramatic progress towards appearance capture and novel view synthesis, particularly for static scenes [1, 5, 27, 34, 46, 63, 66]. Several recent methods can also capture dynamic scenes and reenact their motion [26, 39, 43, 55, 57]. We use the term “reenacting” to highlight that these methods cannot explicitly control the pose of the dynamic objects. Rather, they replay through the poses that were observed. Re-posing an articulated object—i.e., the explicit manipulation of its pose—requires knowing the location of the joints and how the different parts of the object interact with each other1. Learning to predict the location of joints in 3D is a well-studied task, at least for humans, and it is generally tackled using 2D [16,17,20,45,56,61] or 3D [15,19,23–25,51,69] ground truth information. When not using joints supervision, existing pose manipulation methods rely on a predefined model, that is, a template structure [21, 49]. However, annotations are expensive and object-specific, which is why they are only available for limited classes of objects, such as people or faces [14,41,48].

We aim at re-posing an articulated object from a category not seen before, using only a multi-view video and corresponding foreground mask, as shown in Figure 1. Our approach requires no additional supervision, no prior knowledge about the structure, nor networks pre-trained on auxiliary tasks: we learn the appearance and the structure of the object by just watching it move. Like existing meth-

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1Image-to-image translation methods (e.g., [33]) can also re-pose, but we focus on methods that allow to explicitly define the target pose.
to express explicit pose changes, we treat the articulated object as a set of posed parts, each connected to other parts through joints. However, rather than relying on direct supervision, we note that a joint is a 3D point around which a part must rotate to produce the piece-wise, rigid deformation observed in the input images. This allows us to get indirect supervision for the locations of the joints directly from the image reconstruction loss.

Our approach, inspired by neural implicit representations, is scene-specific and predicts the color and the sign-distance function (SDF) of any 3D point, allowing to generate any desired frame by volumetric rendering [58]. We also learn certain properties of the object explicitly. Specifically, we model the object as a set of ellipsoids. A functional part of the object can be represented by one or more ellipsoids, as shown in Figure 2. We optimize the geometric properties of the ellipsoids, i.e., their size and pose, for each frame of the input sequence. The color and density of a 3D point, then, can be predicted from the combined contribution of the ellipsoids. Because these ellipsoids only afford a coarse approximation of the object, we also estimate a residual with respect to this explicit part-based representation. In addition to regularizing the optimization landscape, this representation provides a key advantage: the relative motion of the parts can be explicitly observed over time, which offers clues on the locations of the corresponding joints. Note that this applies to unobserved categories, and requires no prior knowledge on the number of parts that compose it. Because we do not use any prior on the structure of the object or supervision annotations, our method can re-pose any articulated object from a single multi-view video sequence. The pose of the object can be manipulated by applying the appropriate roto-translation to the different joints. We note that our method does not infer the range of motion of each joint. Figures 1(c) and (d) show examples of object re-posing for different categories, structures, and number of parts—all of which were unknown at training time. Our method

- is the first to learn a re-poseable shape representation from multi-view videos and foreground masks, without additional supervision or prior knowledge of the underlying structure,
- it discovers the number and location of physically meaningful joints—also learned with no annotations, and
- it is structure agnostic and can thus be learned for previously unseen articulated object categories.

- Our reconstruction and re-posing results are on par or better than those of category-specific methods that use prior knowledge.

2. Related Work

2.1. Object Re-Posing and Novel-View synthesis

Synthesizing images of articulated objects under novel poses and viewpoints is critical to several applications. Earlier methods formulated the problem as conditional image-to-image translation [4,9,29,33,42,60,62,68]. Given an image of an object and a target pose, these methods use a generator model to transfer a given image to a target pose. The conditioning pose is usually obtained from 2D keypoints or parametric meshes. However, keypoint or mesh models are available for handful of object categories (e.g., faces, human body, and hands), preventing these methods from generalizing to arbitrary object classes.

More recently, NeRF [34] ignited a wave of research on synthesizing novel views of an object by using a sparse set of multi-view images [1,27,34,38,58,63]. These methods learn an implicit 3D representation that provides the color and density of each point in 3D space. Photorealistic images can then be generated using volumetric rendering. Since the implicit 3D representation they use is continuous and topology-agnostic, these methods can reconstruct arbitrary, static objects. Many follow-up works extend NeRF to model dynamic scenes, using single- or multi-view videos for training [26,39,43,55,57]. However, these methods only “reenact” the video used for training, and do not allow control over the articulated pose. We build on these developments and propose a method that also provides control over the articulated pose of the objects.

To allow reposing the objects, various implicit representations for articulated objects have also been proposed, especially for humans. They allow novel view and pose synthesis, but require ground truth poses [8,36,50], or dense 3D meshes [22,28,40,41,54] annotations for the training image. In contrast, we propose a re-poseable 3D implicit representation trained only from multi-view videos and foreground masks of a previously unseen object category. We simultaneously decompose the parts, estimate the connections between them, and reconstruct the image with no prior information about the structure of the object.

Figure 2: We explicitly represent each object’s part as an ellipsoid centered at \( t_i \) and oriented with \( R_i \) (magenta arrow). We identify the part’s joints from a pool of candidates, \( \xi^0 \). The final reconstruction is obtained by estimating a residual w.r.t. the ellipsoids.
2.2. Discovery of 3D Joints of Articulated Objects

Explicitly re-posing an object is straightforward if the joints locations are given, but localizing the 3D joints is challenging. Ground-truth 3D joints supervision simplifies the problem [15, 19, 23–25, 51, 69]. However, 3D annotations are expensive to gather and, perhaps more importantly, they make the resulting algorithms category-specific. Other works simplify the problem and rely on 2D annotations and multi-view [16, 17, 20, 45, 56, 61] or temporal [37] information for 3D supervision. Although 2D joints are cheaper to annotate, the process is still time-consuming and hard to scale to a large number of objects and classes. To address this, some recent methods aim to discover the joints of articulated objects using self-supervised learning [18, 21, 49]. While these methods show impressive results, they still rely on carefully designed, object-specific templates and/or prior information, which cannot be directly applied to other object classes. Other methods can handle arbitrary objects but provide only 2D landmarks [6, 31, 53, 65]. There exist some works that discover 3D keypoints using self-supervision and multi-view data, but they are limited to rigid objects [52]. In contrast to these methods, our approach discovers 3D joints of articulated objects and does not require any 3D annotations, predefined template, or any other prior knowledge about the object, which makes it category-agnostic. Additionally, most of the aforementioned methods only provide locations for a sparse set of keypoints/joints and do not provide any information about the surface geometry or texture of the object. While some methods provide self-supervised dense part labels, they are limited to 2D information [13, 47]. In contrast, our re-posable shape representation provides dense part labels, 3D surface geometry, as well as the texture of each part (implicitly).

Our work is also related to the recent methods for 3D shape representation that use implicit functions [3, 10, 11]. These methods represent a deformable 3D shape as a combination of simple shape elements, e.g., 3D Gaussians (where the level set is an ellipsoid). Each element contributes to the implicit surface of the shape. However, these methods cannot learn surface textures, they require the ground truth 3D shape for training, and do not learn the physical connectivity between parts, which prevents explicit re-posing.

3. Method

3.1. Overview

Our method takes as input a sequence of \( T \) multi-view, posed images of an articulated, moving object, \( O \), and associated masks indicating its silhouette. From those, we learn to render novel views of \( O \). We also discover plausible joints that allow us to render \( O \) in a new pose and from a novel viewpoint, without any additional supervision. We use a hybrid representation of the object that combines an explicit rough approximation of its body, and a subsequent implicit refinement.

We represent \( O \) explicitly as a set of \( P \) parts, each approximated with an ellipsoid, see Figure 2. Rather than assuming \( P \) to be known, we over-segment the object and subsequently merge the different parts as needed (Section 3.5.2). The ellipsoid representing part \( i \) is parametrized with its three-dimensional radius \( r_i \). (Throughout the paper, we use bold for vectors and matrices.) Its pose at time \( t \) is represented by the translation of its center of mass, \( t_i(t) \), and a rotation matrix, \( R_i(t) \). To discover and localize the object’s joints, which define the relationship between different parts, we observe that a 3D point is a meaningful joint if roto- translating a part around it explains a pose change in the reconstructed image.

Our method consists of two trainable modules. The first estimates the pose of each part, for each frame \( t \in [1, T] \) (Section 3.2). The second learns the implicit representation of the appearance and the residual with respect to the
explicit surface of $\mathcal{O}$ (Section 3.3). This module can be queried for the color and signed-distance function of points in 3D, which allows us to render the output view by integrating their contribution [34, 58] (Section 3.4). Further, given the ellipsoids learned at a given iteration, we also discover the underlying structure (Section 3.5), which we use as regularization during training, and to re-pose the object when the training is completed. Figure 3 shows an overview of our method.

3.2. Pose Estimation

As shown in Figure 2, we represent each part of the object $\mathcal{O}$ as an ellipsoid $e_i$, such that their union, $\mathcal{E}$, approximates the object’s 3D shape $\Omega$:

$$\mathcal{E} = \bigcup_{i=1}^{P} e_i \approx \Omega. \quad (1)$$

Each ellipsoid has a learnable three-dimensional radius parameter $r_i$. Using the frame id $t$ as input, we train an MLP, $\mathcal{T}_\Theta$, that outputs the global rotation $R_i(t)$ (represented with a $3 \times 3$ rotation matrix) and translation $t_i(t)$ of each $e_i$. Following common practice [34], rather than feeding $t$ to $\mathcal{T}_\Theta$ directly, we use positional encoding $\gamma(t) = \{\cos(\alpha t)\}_{\alpha=1:50}$. Since we overfit our system to a single scene, we can directly optimize the rotation and translation of each part in the global coordinate system, for each time frame:

$$\mathcal{T}_\Theta : \gamma(t) \rightarrow \{R_i(t), t_i(t)\}_{i=1:P}. \quad (2)$$

By predicting rotations and translations in the global coordinate system, we naturally force the pose of the object to be estimated consistently across views.

3.3. Shape and Appearance Decoder

Similar to NeuS [58], we seek to estimate the color, $c$, and signed-distance functions (SDFs), $d$, at any 3D point, $x^g$, to perform volumetric rendering. Since the ellipsoids alone cannot accurately capture the object’s shape, we use a second MLP, $S_\Theta$, to predict a residual. To ensure that the final shape does not deviate significantly from $\mathcal{E}$, we represent this as a residual SDFs, $\Delta d$, which is bounded by construction.

We first convert the query point $x^g$, expressed in global coordinates, to the local coordinate system of each part

$$x_i(t) = (R_i(t))^{-1}(x^g - t_i(t)), \quad (3)$$

and we apply weighted positional encoding [36] to compute a feature vector

$$f = \text{CAT}\{w^{\text{PE}}_i \gamma(x_i(t))\}_{i=1:P}, \quad (4)$$

where $\text{CAT}$ is the concatenation operation. The weights in Equation 4 are computed as

$$w^{\text{PE}} = \text{softmax}\left\{-s^{\text{PE}} d_i\right\}_{i=1:P}, \quad (5)$$

where $d_i = \text{SDF}_i(x_i(t), e_i)$, and $s^{\text{PE}}$ is a learnable temperature parameter for the softmax. The SDFs from the ellipsoids can be computed directly from their radii and poses (see Supplementary). Note that $f$ effectively subsumes the current estimates of the ellipsoids, their pose, and the location of the sampled point. We then feed $f$ to a second MLP

$$S_\Theta : f(x^g) \rightarrow (c, \Delta d)|_{x^g}, \quad (6)$$

where $c$ is color of $x^g$, and $\Delta d$ a residual with respect to the SDFs estimated from the ellipsoids, which we compress as

$$\Delta d = d_{\text{max}} \tanh(s \Delta d), \quad (7)$$

where $d_{\text{max}}$ is the maximum value of $\Delta d$ and $s$ is a learnable scale parameter. The final SDF can be computed as

$$d = -\frac{1}{s} \text{logsumexp}\left\{-s^d d_i\right\}_{i=1:P} + \Delta d, \quad (8)$$

where $s$ is a learnable scaling factor. Following NeuS [58], we compute the S-density from the signed-distance function, $d$, and use it with the color estimate of the 3D point to volume render the desired image. We also regularize the SDF with the Eikonal loss [12]:

$$\mathcal{L}_{\text{SDF}} = \mathbb{E}[(||\nabla d||_2 - 1)^2]. \quad (9)$$

We predict SDFs rather than densities because $\Delta d$ is bounded (Equation 7) and thus naturally bounds the difference between the surface positions of object $\Omega$ and the ellipsoid approximation, $\mathcal{E}$.

3.4. Rendering

The color of an output pixel can be predicted by volumetric rendering using the signed-distance function, as proposed in NeuS [58], and which we briefly describe here for completeness. The discrete opacity of the $j$-th point along the 3D ray corresponding to the output pixel can be computed as

$$\alpha_j = \max \left(\frac{\Phi_s(d_j) - \Phi_s(d_{j+1})}{\Phi_s(d_j)}; 0\right), \quad (10)$$

where $d_j$ is the signed-distance function at the point (represented in global coordinates) and $\Phi_s$ is a sigmoid function. From Equation 10 we compute the accumulated transmittance along the ray

$$T_j = \prod_{k=1}^{j-1} (1 - \alpha_k), \quad (11)$$

which we use to estimate the color of the output pixel as

$$\hat{c} = \sum_j T_j \alpha_j \hat{c}_j. \quad (12)$$
Reconstruction and part segmentation rendered from novel perspectives.

Similarly, the foreground mask can be rendered as \( \tilde{\Phi} \), and this foreground can then be rendered from novel perspectives. Animated figure. Figure 4:

Two observations. First, a point inside part \( e \) is likely to have a different relative pose throughout the sequence than a point in another part. Second, the joint between two parts that changes most quickly is likely to be a joint that connects multiple parts.

3.5. Discovery of the 3D Joints

So far, we have described the object’s parts as an unstructured set of ellipsoids \( \mathcal{E} \). That is, each part’s transformation is applied in the global coordinate frame, and the parts act independently of each other. However, because these ellipsoids represent the object explicitly, they allow us to discover the underlying structure. Specifically, we make two observations. First, a point inside part \( e_i \) that coincides with (is close to) a point in part \( e_j \) as the relative pose between the two parts changes, is likely to be a joint that connects the two parts. We detail how we leverage this insight in Section 3.5.1. Because we do not know the number of parts a priori, we start by over-segmenting the object. Our second insight is that two connected parts that maintain the same relative pose throughout the sequence can be merged: the joint between them is not necessary to explain the poses observed in the input sequence, Section 3.5.2.

3.5.1 Structure Discovery

We start by sampling \( N \) equally spaced joint candidates, \( \xi^n_t \), for each part \( e_i \), see Figure 2. We provide more details about the sampling in the Supplementary. In order to discover

\[ L^\text{photo} = E_{\text{ray}}[\sum_{i,j} \| \tilde{\Phi} - \Phi \|_2^2 + \| \tilde{M} - M \|_2^2] \]  \tag{13}

We refer to the paper by Wang et al. for more details [58].

3.5.2 Part Merging

Rather than assuming prior knowledge on the total number of parts, we over-segment the object and merge redundant parts. Specifically, we combine parts that are static connections we first compute the distance between all candidates, for every joint pair \((i, j)\), and over all frames

\[ l_{i,j}^{m,n} = \sum_{t} \left( \| \xi^m_t - \xi^n_t \|_2 + \lambda_1 \| t_i - t_j \|_2 \right) \]  \tag{14}

where the second term penalizes connections between parts that are far from each other, \( \lambda_1 \) is a regularization coefficient, and \( t \) is the frame id. To prevent the distance from changing too quickly, we smooth it across iterations

\[ \tilde{l}_{i,j}^{m,n}(\tau + 1) \leftarrow (1 - \epsilon) \cdot \tilde{l}_{i,j}^{m,n}(\tau) + \epsilon \cdot l_{i,j}^{m,n}(\tau) \]  \tag{15}

where \( \epsilon \) is a momentum, and \( \tau \) the training iteration. We compute the cost of connecting parts \( i \) and \( j \) as

\[ l_{i,j} = \min_{n,m} l_{i,j}^{m,n} \]  \tag{16}

We sort the list of \( l_{i,j} \)’s for all parts in ascending order and traverse it to connect the parts that are closest (lowest cost). We assume the object’s structure, \( \Gamma \), to be an acyclic graph, so we require that there be a path between any two joints, and we do not allow connections that would create loops. We do not connect parts that violate this requirement, even if their \( l \) is the next lowest. This procedure allows us to determine the structure of any articulated object that can be modelled as an acyclic graph. We also compute the overall cost associated with a particular configuration \( \Gamma \)

\[ L_\Gamma = \sum_{(i,j) \in \Gamma} l_{i,j} \]  \tag{17}

which we use to regularize our training procedure (see Section 3.6). Figure 5 shows the typical quality of the structure we identify. Note that a part can connect to multiple parts.
with respect to each other throughout the sequence, see Figure 5. Differently put, we only preserve the articulations that are necessary to explain a change of pose in the input videos. The relative position between parts can be computed as

$$ R_{i,j} = R_{i}^{-1} R_{j} $$

$$ t_{i,j} = R_{i}^{-1} (t_j - t_i) $$

We can then measure the relative motion as

$$ D_{i,j} = \sigma(t_{i,j}) + \lambda \sigma(t_{i,j}) $$

where $\sigma$ is the standard deviation over time. We compute Equation 18 for all pairs of parts and iteratively merge those for which $D_{i,j}$ is small. A few steps of this process are shown in Figure 5. We also define a merging loss

$$ L_{merge} = \frac{1}{P^2} \sum_{i \neq j} D_{i,j} \Phi_{1} \left( \frac{D_i - D_j}{\bar{D}} \right), $$

where $\bar{D}$ is a hyperparameter, and $\Phi_{1}$ is a sigmoid function.

### 3.6. Training Strategy and Regularization

We train our system on a single scene, and in an end-to-end fashion. The process optimizes also for the parts’ radii $\{r_i\}$, in addition to training the parameters of the two MLPs. To help stabilize the training, we progressively increase the number of frames used for training as the training converges. This strategy yields a reasonable initialization of the structure, which is then adjusted to capture a consistent part decomposition and structure over the entire video.

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**Figure 7:** Animated figure. Re-posing comparison against the baseline methods, Section 4.3. For Kundu et al. we use the neutral body model.

Our loss function comprises several terms, including $L_{SDF}$, $L_{photo}$, $L_{\Gamma}$, and $L_{merge}$ in Equations 9, 13, 17, and 19, respectively. However, we only add $L_{merge}$ after all the frames are added to the training. We describe additional regularization terms in the following, and we evaluate the contribution of each term in Section 4.5. The final loss is a weighted sum of these terms, see Supplementary.

**Ellipsoidal Surface Regularization** Our explicit use of ellipsoids to approximate the shape of the object allows us to sample points from the surface at a low cost. The projection of sampled surface points onto the image should cover the whole foreground mask of the object, and no pixels outside of it. We encourage this by minimizing the chamfer distance between the points sampled from the surface and the points sampled from the foreground mask:

$$ L_{E} = \frac{1}{N_E} \sum_{i} \min_{j} \left\| p_{E} - p_{M} \right\|^2 $$

$$ + \frac{1}{N_M} \sum_{j} \min_{i} \left\| p_{E} - p_{M} \right\|^2, $$

where $p_{E}$ are the coordinates of points randomly sampled from the surface of $E$ and projected into the image space, $N_E$ is their number, $p_{M}^{GT}$ are the coordinates of points randomly sampled from the mask $M_{GT}$, and $N_M$ is their number.

**Separation Loss** We further discourage the parts themselves to be concentrated in a single region by penalizing small distances between their centers:

$$ L_{separation} = \frac{1}{P^2} \sum_{i \neq j} \exp \left( \frac{||t_i - t_j||^2}{2\sigma^2} \right), $$

where $\sigma$ controls the scale of the distances to be regularized.

### 4. Evaluation and Results

We evaluate our method’s ability to re-pose objects and estimate their joints—both qualitatively and quantitatively.
4.1. Pose Manipulation

One critical advantage of our explicit representation is the ability to manipulate the pose of previously unseen categories without prior knowledge: we can directly use the structure we discover by watching the object move. Given the frame id of a particular sequence, we manipulate the corresponding pose by applying hand-crafted rotations and translations to each of the parts. To showcase our method’s ability to discover the structure, we render a small dataset of seven structurally diverse robots. We provide more details about the rendered data in the Supplementary. Figures 1 and 6 show re-posing examples across different robots. Note how the structure, as well as the number of parts and joints, is significantly different across all of these examples. We do not estimate the range of motion at each joint, and leave it up to the user to define plausible poses.

4.2. Pose Manipulation for Humans

The structure our method discovers is plausible, as it allows for accurate re-posing, but it may not coincide exactly with the physical structure of the object. For a quantitative evaluation we focus on humans, because of the rich literature of methods and annotated data for this category. Specifically, after training our method, we use a subset of the training frames to learn a linear transformation from the joints of an SMPL model [30] to ours. Since the ZJU-MoCap dataset [41] has ground truth SMPL annotations, we can use this mapping to re-pose our model to target frames not observed in training, as shown in Figure 7. We use five subjects from the ZJU-MoCap dataset. For each sequence we use the first 80% of frames for training and the remaining for testing. The details of the mapping to and from the SMPL model are in the supplementary. Note that this mapping is for evaluation purposes only—our method allows for direct manipulation and does not need a SMPL model, as shown in Figure 6. Table 1 provides evidence of the reconstruction quality of our re-posed renderings for the test frames, averaged over all the five subjects. We report numbers for our model before and after merging (Section 3.5.2).

Merging causes a small performance hit because it reduces the expressiveness (DOF) of the representation. However, even after merging, the performance remains competitive.

4.3. Baselines Description and Evaluation

A direct numerical comparisons with the state-of-the-art is impossible: ours is the first work that allows to explicitly re-pose a dynamic object from a previously unseen category, without supervision (other than multi-view supervision), or prior knowledge of the underlying structure. Moreover existing methods are not scene-specific. The methods by Schmidtke et al. [49] and by Kundu et al. [21], both of which assume a template and only work for humans, are the closest existing solutions for unsupervised, direct pose manipulation. Although they tackle a more constrained task, we use them as inspiration for baselines that allow for a quantitative evaluation.

Both Schmidtke et al. [49] and Kundu et al. [21] employ a CNN-based encoder, which allows them to work on scenes not seen in training. This gives an unfair advantage to our method, which overfits to a specific sequence. Therefore, we propose the modifications in Figure 8, which allow us to train both methods for a specific sequence, like ours.

We modify the method by Kundu et al. by swapping their CNN-based encoder with an MLP that overfits the SMPL parameters to each frame. These parameters are then used to adapt the SMPL mesh to the pose in the frame. We train the MLP by enforcing that the color of corresponding vertices in different frames match. After convergence we compute the color of all the vertexes of the SMPL model by averaging the colors of the corresponding pixels in all the input frames. Re-posing their solution, then, reduces to ma-
Figure 9: **Animated Figure.** The joints our method discovers are plausible and stable across the sequence.

manipulating the SMPL parameters. To adapt the approach of Schmidte et al., we replace their 2D template with a 3D template and their CNN encoder with an MLP that learns how to deform the 3D template to match the pose at the given time frame. Given a viewport we can project the template to a 2D representation, which can be converted to an RGB image with a second network. We denote both baselines with a * to indicate they are adapted from their original versions. A few considerations are in order. First, the architecture of both MLPs is the same as ours, and the number of the parameters to be predicted comparable. Second, while we make those methods scene-specific to remove our advantage, they still only work for people and still use a template or an SMPL model, like the original versions. They are our best effort at a fair comparison. We train both models on the same train/test split of the same five subjects we use for our method. For Kundu et al. we use the neutral SMPL body model. A qualitative comparison can be seen in Figure 7. Table 1 reports LPIPS [64] and SSIM [59] for both reconstruction (i.e., same pose as in one of the input frames, but different view) and re-posing. Our method is on par or slightly better than these baselines despite making no assumptions about the structure of the object.

### 4.4. Joint Estimation Evaluation

Our method discovers plausible joints. That is, they also to re-pose the object consistently with the input images, but they may not exactly coincide with the physical joints. Figure 9 offers a qualitative evaluation: our 3D joints appear to closely follow the physical joints locations and they are stable over time. For a quantitative evaluation, we use one tenth of the frames in each sequence to compute a linear mapping from our joints and joints candidates to the joints of the SMPL model provided by the dataset, as is common practice for methods that discover landmarks [31, 53, 65]. The details of the algorithm that regresses this mapping are in the Supplementary. We apply the linear mapping to the remaining frames to compute the mean per joint position error (MPJPE) [14]. We also compare with the baselines defined in Section 4.3. For Kundu et al. we learn a linear mapping from the predicted SMPL vertices to the GT joints provided by the dataset, while for Schmidte et al. we compute the same linear mapping as for our method. Once again, our method performs on par, and sometimes even better despite the additional information available to the baseline methods.

### 4.5. Ablation

In our first ablation study we evaluate the effect of each loss term to the overall performance. We use subject 366 from the ZJU-MoCap dataset and train our model from scratch by disabling one loss term at the time. The results are shown in Table 2. We note that the additional terms have a marginal effect on the quality of the rendered images, but they do reduce the joints estimation error measurably. In our second experiment, we evaluate the importance of training $S_{\theta}$ to predict an SDF residual $\Delta d$, instead of the SDF $d$ itself, as done in Neural-GIF [54]. Table 2 confirms that predicting residual is critical to both the image reconstruction quality and the joints estimation.

### 5. Limitations

Our method requires multi-view videos, which can limit its applicability. All the scenes in the paper use six cameras around the object. The four viewpoints available in the Human3.6M dataset [14] do not provide sufficient coverage for our method. An additional constraint is that we can only re-pose parts that move relative to each other in the training sequence—we cannot infer what we cannot see. Our solution does not tackle the problem of defining plausible motion ranges around the joints and focuses on spherical joints, leaving different types of joints, such as sliding joints, for future work. We also observed that the randomness of the structure initialization can sometimes make the training unstable; we leave it to future work to find a more elegant solution than simply re-initializing it when this happens.

### 6. Conclusions

We presented a method that discovers the structure of an articulated object from arbitrary categories, by watching it move in a multi-view video. It can then render the object from novel views and even directly manipulate its pose. Our method works for arbitrary articulated objects, as we show using robots with varying structures.

### Table 2: Ablation study.

|                      | Full | $+L_{\text{merge}}$ | $-L_s$ | $-L_{\text{separation}}$ | $-\Delta d$ |
|----------------------|------|---------------------|--------|--------------------------|------------|
| Novel view LPIPS↓    | 0.061| 0.062               | 0.062  | 0.062                    | 0.065      |
| Novel view SSIM↑     | 0.959| 0.958               | 0.958  | 0.959                    | 0.959      |
| Novel pose LPIPS↓    | 0.065| 0.065               | 0.069  | 0.069                    | 0.067      |
| Novel pose SSIM↑     | 0.954| 0.953               | 0.951  | 0.952                    | 0.953      |
| Joints MPJPE (mm)↓   | 8.70 | 10.25               | 9.35   | 12.13                    | 9.72       | 22.14 |
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A. Implementation details

A.1. Pose Estimation (Section 3.2)

MLP $T_\Theta$ takes the positionally encoded frame id as input and outputs a vector of 9P dimensions. The 3P dimensions correspond to each element of $t_i$, and the remaining 6P dimensions correspond to the rotation matrix calculation, please refer to Zhou et al. [67], Section B. $T_\Theta$ is a 4-layer MLP with a hidden dimension of 256.

A.2. SDF Computation of an Ellipsoid (Section 3.3)

The merit of using ellipsoids as the representation of the parts is that their SDFs are continuous functions and can be computed cheaply. In this subsection, we explain how to calculate the SDF of an ellipsoid. First, the surface of an ellipsoid of radii $\mathbf{r}$ is given by

$$f(x, \mathbf{r}) = \frac{x_1^2}{r_1^2} + \frac{x_2^2}{r_2^2} + \frac{x_3^2}{r_3^2} = 1,$$

where position $x = (x_1, x_2, x_3)$ and radii $\mathbf{r} = (r_1, r_2, r_3)$. We calculate the SDF of an ellipsoid as follows. First, from the query point $x$, we find the nearest ellipsoid surface point $x_e$. Since this cannot be solved analytically, we use Lagrange’s multiplier method and Newton’s method to find the point. The cost function $\mathcal{L}$ is defined as

$$\mathcal{L} = |x - x_e|^2 - \lambda(f(x_e, \mathbf{r}) - 1),$$
and we solve $\frac{\partial C}{\partial x} = \frac{\partial C}{\partial \lambda} = 0$. This can be transformed into the following equations

$$\begin{cases} x_e = r^2 \odot (r^2 + \lambda) \odot x \\ \| r \odot (r^2 + \lambda) \odot x \|_1^2 = 1, \end{cases}$$

(24) (25)

where $\odot$ is element-wise division, $\odot$ is element-wise product, and $a^2 = a \odot a$. We use Newton’s method to find the largest solution for $\lambda$ in Equation (25) and substitute it into Equation (24) to get $x_e$.

The distance between the searched point and the input point $x$ is the absolute value of the SDF, which has a negative sign when $x$ is inside the ellipsoid and a positive sign when it is outside:

$$\text{SDF}(x, r) = \text{sign}(f(x, r) - 1) |x - x_e|_2.$$  

(26)

However, since $x_e$ is computed numerically, the gradient is not propagated to $r$. Therefore, we re-parametrize $x_e$ using $r$ by projecting $x_e$ onto the surface of the unit sphere and back onto the surface of the ellipsoid.

$$\tilde{x}_e = (x_e \odot r) \text{detach()} \odot r,$$

(27)

where $\odot$ is element-wise division, $\odot$ is element-wise product, and $\text{detach()}$ is a stop-gradient operation.

Finally, the differentiable SDF of an ellipsoid is computed as,

$$\text{SDF}(x, r) = \text{sign}(f(x, r) - 1) |x - \tilde{x}_e|_2.$$  

(28)

A.3. Joint Candidates (Section 3.5.1)

In this subsection, we explain the details of the joint candidates defined in the Section 3.5.1 in the main paper. When a point inside one ellipsoid $e_i$ is close to a point inside another ellipsoid $e_j$ throughout the entire video, the point is considered to be a joint between parts $i$ and $j$. To find these points, we create several joint candidate points $\{\xi^n_{i,j}\}_{n=1:N}$ inside the ellipsoids in advance, and minimize the distance between them. We define six candidates inside each ellipsoid in the local coordinate, as follows

$$\hat{\xi}^n_i = r_i \odot \xi^n,$$

(29)

where $\xi^n \in \{(\pm \frac{3}{4}, 0, 0), (0, \pm \frac{3}{4}, 0), (0, 0, \pm \frac{3}{4})\}$. This is then transformed into the global coordinate system using the rotation and translation of each part

$$\xi^n_{i,j} = R_i \hat{\xi}^n_i + t_i.$$  

(30)

A.4. Frame scheduling (Section 3.6)

In order to stabilize the training, we progressively increase the number of frames used for training. First, we use the first $T_0$ frames of data to train for $\tau_0$ iterations. Then, the number of frames used for training is increased linearly so that all frames $T$ of the video are used at $\tau_1$ iteration. After that, all frames are used for training until $\tau_{\text{final}}$. In the experiment using human data, we set $T_0 = 10$, $\tau_0 = 10k$, $\tau_1 = 80k$.

A.5. Loss (Section 3.6)

The loss function is a weighted sum of $\mathcal{L}_{\text{SDF}}$, $\mathcal{L}_{\text{photo}}$, $\mathcal{L}_{\Gamma}$, $\mathcal{L}_{\text{merge}}$, $\mathcal{L}_{\text{E}}$, and $\mathcal{L}_{\text{separation}}$:

$$\mathcal{L}_{\text{total}} = \lambda_{\text{SDF}} \mathcal{L}_{\text{SDF}} + \lambda_{\text{photo}} \mathcal{L}_{\text{photo}} + \lambda_{\Gamma} \mathcal{L}_{\Gamma} +$$

$$\lambda_{\text{merge}} \mathcal{L}_{\text{merge}} + \lambda_{\text{E}} \mathcal{L}_{\text{E}} + \lambda_{\text{separation}} \mathcal{L}_{\text{separation}}.$$  

(31)

We used $\lambda_{\text{SDF}} = 0.2$, $\lambda_{\text{photo}} = 1$, $\lambda_{\text{merge}} = 0$, $\lambda_{\text{E}} = 600$, and $\lambda_{\text{separation}} = 1$. We gradually increase $\lambda_{\Gamma}$ from 2 to 50 until iteration $\tau_0$ for training stability. From iteration $\tau_2$, we set $\lambda_{\text{merge}} = 5$ and train the model until $\tau_{\text{final}}$. We set $\tau_2 = 150k$.

A.6. Other Training Details

The other hyper-parameters were set as $d_{\text{max}} = 0.02$, $\lambda_1 = 0.02$, $\lambda_3 = 3$, $D = 0.1$, $\epsilon = 0.01$. For the weighted positional encoding in Equation 4 in the main paper, we apply positional encoding [35] to spatial locations $x_i$ with 6 frequencies following the training setting of NeuS [58].

We used AdamW optimizer [32] with learning rate 0.0003, and $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\lambda = 0.005$. All training images are resized to $512 \times 512$. We train the model up to $\tau_{\text{final}} = 200k$ iterations with a batch size of 16. We randomly sample 384 rays from each image for human data, where $P$ is set to 20. Training takes about 48 hours on a single NVIDIA A100 GPU.

A.7. Pose Manipulation (Section 4.1)

Since our method estimates explicit joint relationships between parts, we can freely manipulate the pose of the object. First, the position of the final joints $\xi_{i,j}$ is defined as the midpoint of the candidate points $\xi^m_i$ and $\xi^j_i$ connected in Equations 16 and 17 of the main paper:

$$\xi_{i,j} = \frac{1}{2}(\xi^m_{i,j} + \xi^j_{i,j}) \quad \text{s.t.} \quad (m, n) = \arg \min_{m,n} \Gamma_{i,j}^{m,n}.$$  

(32)

By manually rotating the part $i$ or $j$ and its children parts around this joint $\xi_{i,j}$, the pose of the object can be freely changed, and novel rotations and translations for each part can be obtained $\{R_i, t_i\}^\text{n}$. To render the novel pose image, we directly input $\{R_i, t_i\}^\text{n}$ to the second network $S_\Theta$.

A.8. Baselines (Section 4.3)

Kundu* et al. [21] Their original model estimates SMPL parameters in an unsupervised manner as follows. First, a CNN-based encoder receives an image and estimates the parameters of the SMPL model. Based on the estimated parameters, the SMPL mesh is deformed and a pixel value of the image is assigned to each vertex according to its position in the image. The model is trained to match the colors of the estimated mesh vertices from different images of the
same person at different times. By using CNN-based encoder, they can reconstruct the mesh from unseen monocular images. However, our method uses videos of specific scenes from multiple viewpoints, which gives us an unfair advantage. In order to allow for a fair comparison between our method and theirs, we replaced their CNN-based encoder with an MLP $T_{θ}^{\text{kundu}^*}$ that takes frame id as input and estimates SMPL parameters for each frame.

$$T_{θ}^{\text{kundu}^*} : \gamma(t) \rightarrow R(t), t(t), \theta(t), \beta,$$  \hspace{1cm} (33)

where $R(t)$ is a global orientation, $t(t)$ is a global translation, $\theta(t)$ is joint poses, and $\beta$ is a shape parameters. This MLP allows Kundu* et al. to overfit to the specific video sequence, like our method does. Please note that $\beta$ is not time dependent. The structure of the MLP $T_{θ}^{\text{kundu}^*}$ is the same as that of $T_{θ}$ used in the proposed method except for the output dimension. Since the authors do not publish their training implementation, all modules and loss functions are our replicated implementation. For the human pose prior, instead of training the adversarial auto-encoder, we used the pre-trained human pose prior from Bogo et al. [2]. Also, since our experimental setup uses multi-view videos and overfits to a single subject, we do not use reflectional symmetry or shape-consistency loss. Please refer to Kundu et al. [49] for more details. In addition, since human foreground masks are available in our experimental setup, we use a differentiable renderer [44] to render the mask of the mesh and train it so that the L2 norm with the GT foreground mask is small. We apply the same frame scheduling as in Section A.4 for training stabilization.

After training the model, we assign colors to the vertices of the SMPL mesh for novel view and pose synthesis, where we average the estimated vertex color for various frame ids and viewpoints using the learned SMPL poses.

Schmidtke* et al. [49] Their original model trains the deformation of a 2D template of a person’s structure in an unsupervised manner using image reconstruction. They use a CNN-based encoder to estimate the 2D deformation parameters. To extend the method to 3D, we replaced the 2D templates with 3D templates, where the shape is approximated with 3D gaussians. For a fair comparison, we also replaced the CNN-based encoder with an MLP $T_{θ}^{\text{schmidtke}^*}$ that takes a frame id as input and outputs the deformation parameters of the template in the global coordinate, as in Kundu* et al.

$$T_{θ}^{\text{schmidtke}^*} : \gamma(t) \rightarrow \{R_i(t), t_i(t), s_i\}_{i=1:18},$$  \hspace{1cm} (34)

where $R_i(t)$ and $t_i(t)$ are rotation and translation for each part, and $s_i$ is 3D scale parameters for each part. We replace the affine transformation $Θ_i$ defined in Equation 3 in Schmidtke* et al. [49] with a physically meaningful transformation

$$Θ = \begin{bmatrix} s_1 R_{1,1} & s_1 R_{1,2} & s_1 R_{1,3} & t_1 \\ s_2 R_{2,1} & s_2 R_{2,2} & s_2 R_{2,3} & t_2 \\ s_3 R_{3,1} & s_3 R_{3,2} & s_3 R_{3,3} & t_3 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \hspace{1cm} (35)$$

Please note that $s_i$ is not time dependent. The deformed 3D template is projected onto a 2D heatmap using the viewpoint of the training image, and then transformed into an RGB image using a second CNN-based network. Since the model is overfitted on a single scene, we do not input the reference frame to the second network, but only the 2D heatmap. We modified the implementation based on their public training code\(^2\), and the loss function used for training is exactly the same as the original. Please refer to Schmidtke et al. [49] for more details.

We apply the same frame scheduling as in Section A.4 for training stabilization.

A.9. Regression of GT SMPL Pose (Section 4.2, 4.4)

For human re-posing we learn a linear mapping from the GT SMPL poses to estimated joints and for joint evaluation we learn a mapping from the estimated joints to the GT SMPL poses.

Mapping from SMPL For re-posing, we perform a regression from the GT SMPL mesh to our part pose $R_i$ and $t_i$. First, for all frames of the training data, we optimize the linear transformation $X$ from the mesh vertices $V(t)$ to the concatenation of the learned part centers and the candidate points $P(t) = \text{CAT}\{t, ξ_i^1, ..., ξ_i^N\}_{i=1:P}(t)$ using the least-squares method

$$\min_X \left( \sum_i |X V(t) - P(t)|_F + \frac{1}{2} \lambda |X|_F \right). \hspace{1cm} (36)$$

When re-posing with SMPL meshes, we compute the part centers and candidate points $P^{\text{new}} = \text{CAT}\{t^{\text{new}}, ξ_i^{1, ..., ξ_i^N}\}_{i=1:P}^{\text{new}}$ corresponding to the novel pose SMPL mesh $V^{\text{new}}$ using the learned linear transformation $X$,

$$P^{\text{new}} = X V^{\text{new}}. \hspace{1cm} (37)$$

The part centers $t_i^{\text{new}}$ of the new pose are obtained by extracting the corresponding elements of $P^{\text{new}}$. The rotation matrix $R_i^{\text{new}}$ is obtained by solving the following optimization:

$$\min_{R_i^{\text{new}}} |R_i^{\text{new}} \hat{Ξ}_i - \hat{Ξ}_i|_F \quad s.t. \quad (R_i^{\text{new}})^T R_i^{\text{new}} = I, \hspace{1cm} (38)$$

\(^2\)https://github.com/lschmidtke/shape_templates
where \( \hat{\xi}_i = [\xi_1^i, \ldots, \xi_N^i], \xi_i = [\xi_1^i - t_i, \ldots, \xi_N^i - t_i] \). By using the resulting \( t_{\text{new}}^i \) and \( R_{\text{new}}^i \) into the second network \( S_\Theta \) directly, we can re-pose the object.

Similarly, for the re-posing of the baseline Schmidtke* et al. [49], the part center \( t_i \) of the 3D template and the points around it

\[
\xi^n_i \in \{ t_i \pm rR_1^i, t_i \pm rR_2^i, t_i \pm rR_3^i \}
\]

are used to learn the same linear mapping, where \( R_i = [R_1^i, R_2^i, R_3^i] \) and \( r = 0.1 \).

**Mapping to SMPL** To evaluate the joint, we regress the translation \( J(t) = \text{CAT}\{j_{i}\}_{i=1:23}(t) \) of the GT SMPL joints at frame \( t \) from the learned object poses at \( t \), where \( \text{CAT} \) is the concatenation operator. We obtain a linear mapping \( X \) from the learned poses to the SMPL joints by solving the following optimization problem:

\[
\min_X \left( \sum_{t \in T_{\text{train}}} |XP(t) - J(t)|_F + \frac{1}{2} \lambda |X|_F \right), \quad (40)
\]

where \( T_{\text{train}} \) is the set of frames used for this optimization, which are uniform sample of 10% of the available frames.

For joint evaluation, a learned linear transformation \( X \) was applied to the remaining frames to compute the mean per joint position error (MPJPE) [14] between the regressed joint position and the GT joint position.

Similarly, for the baseline Schmidtke* et al. [49], we learn a linear mapping from the part center \( t_i \) of the 3D template and the points around it \( \xi^n_i \) defined in Equation 39 to the GT SMPL joints.

For the evaluation of Kundu* et al. [21], we learn a linear regression \( X \) from the learned SMPL mesh vertices \( V_{\text{Kundu}} \) to the GT SMPL joints

\[
\min_X \left( \sum_{t \in T_{\text{train}}} |XV_{\text{Kundu}}(t) - J(t)|_F + \frac{1}{2} \lambda |X|_F \right). \quad (41)
\]

We evaluated both models in the same way as ours.

**B. Robot dataset**

In order to demonstrate the applicability of our method to objects with various structures, we created a dataset of robots with seven different structures, see Figure 10. The dataset consists of 1000 frames of synchronized video with 20 viewpoints per robot. We sampled five of these views and trained on the first 300 frames of each video.

In order to generate the dataset we use a recent python-based renderer, NViSII [35]. We use robots that are freely available and have URDF associated with 3D meshes. In order to animate the robot, we use PyBullet [7]. The robot is given random joint goals, and once it reaches these goals, we repeat the process of giving it random joint goals. We place 20 fixed cameras on the hemisphere at a fixed distance from the robot, and we add a warm sunlight to add more light to the scene. Each frame is rendered with 2000 samples per pixel at 512×512 resolution. We use the OptiX denoiser to clean the final renders to provide noise free images. We plan to make both the datasets and the scripts to generate the multiview animated objects available upon acceptance.

**C. Additional Results for Parts Merging**

Additional results of parts merging are shown in Figure 11 (a). The results confirm that meaningful parts and the structure are obtained by merging. To show the effect of \( L_{\text{merge}} \), we show the merging results when it is disabled in Figure 11 (b). It can be seen that by using \( L_{\text{merge}} \), we can appropriately pull parts together that have the same relative motion, and learn more meaningful decomposition of parts.
Figure 11: (a) Additional results for part merging. From left to right, we show the initial joints and structure, the joints and structure after merging, and the connection between the centers of the parts. Since there is no joint at the endpoint, the center of the part is connected instead (red lines). A polygonal path indicates a part that is connected to multiple parts. The centers of the parts are shown for clarity. (b) Joints and part centers obtained when $L_{\text{merge}}$ is disabled.