

CoNeRF: Controllable Neural Radiance Fields

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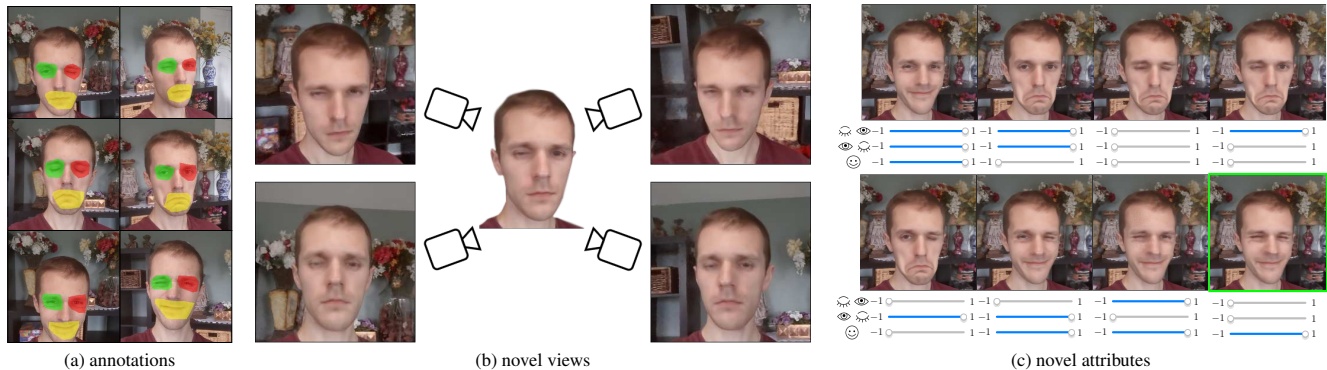


Figure 1. **Teaser** – We train a controllable neural radiance field from multiple views of a dynamic 3D scene, under varying poses and attributes; in this example eye being open/closed and mouth smiling/frowning. Given only six annotations (a), our method provides full control over the scene appearance, allowing us to synthesize (b) novel views and (c) novel attributes, including attribute combinations that were *never seen* in the training data (green box).

Abstract

We extend neural 3D representations to allow for intuitive and interpretable user control beyond novel view rendering (i.e. camera control). We allow the user to annotate which part of the scene one wishes to control with just a small number of mask annotations in the training images. Our key idea is to treat the attributes as latent variables that are regressed by the neural network given the scene encoding. This leads to a few-shot learning framework, where attributes are discovered automatically by the framework, when annotations are not provided. We apply our method to various scenes with different types of controllable attributes (e.g. expression control on human faces, or state control in movement of inanimate objects). Overall, we demonstrate, to the best of our knowledge, for the first time novel view and novel attribute re-rendering of scenes from a single video.

1. Introduction

Neural radiance field (NeRF) [30] methods have recently gained popularity thanks to their ability to render photorealistic novel-view images [28, 35, 36, 50]. In order to widen the scope to other possible applications, such as digital media production, a natural question is whether these methods could be extended to enable *direct* and *intuitive* con-

trol by a digital artist, or even a casual user. However, current techniques only allow coarse-grain controls over materials [53], color [18], or object placement [48], or only support changes that they are designed to deal with, such as shape deformations on a learned shape space of chairs [25], or are limited to facial expressions encoded by an explicit face model [12]. By contrast, we are interested in *fine-grained* control without limiting ourselves to a specific class of objects or their properties. For example, given a self-portrait video, we would like to be able to control individual *attributes* (e.g. whether the mouth is open or closed); see Figure 1. We would like to achieve this objective with minimal user intervention, without the need of specialized capture setups [24].

However, it is unclear how fine-grained control can be achieved, as current state-of-the-art models [36] encode the structure of the 3D scene in a *single* and *not interpretable* latent code. For the example of face manipulation, one could attempt to resolve this problem by providing *dense* supervision by matching images to the corresponding Facial Action Coding System (FACS) [11] action units. Unfortunately, this would require either an automatic annotation process or careful and extensive per-frame human annotations, making the process expensive, generally unwieldy, and, most importantly, domain-specific. Automated tools for domain-

agnostic latent disentanglement are a very active topic of research in machine learning [9, 16, 17], but no effective plug-and-play solution exists yet.

Conversely, we borrow ideas from 3D morphable models (3DMM) [7], and in particular to recent extensions that achieve local control by *spatial disentanglement* of control attributes [32, 46]. Rather than having a single global code controlling the expression of the *entire* face, we would like to have a set of *local* “attributes”, each controlling the corresponding *localized* appearance; more specifically, we assume spatial quasi-conditional independence of attributes [46]. For our example in Figure 1, we seek an attribute capable to control the appearance of the mouth, another to control the appearance of the eye, etc.

Thus, we introduce a learning framework denoted CoNeRF (i.e. Controllable NeRF) that is capable of achieving this objective with just *few-shot* supervision. As illustrated in Figure 1, given a single one-minute video, and with as little as two annotations per attribute, CoNeRF allows *fine-grained*, *direct*, and *interpretable* control over attributes. Our core idea is to provide, on top of the ground truth attribute tuple, *sparse* 2D mask annotations that specify which region of the image an attribute controls, in spirit of Interactive Digital Photomontage [4] and Video Sprites [39]. Further, by treating attributes as latent variables within the framework, the mask annotations can be automatically propagated to the whole input video. Thanks to the quasi-conditional independence of attributes, our technique allows us to synthesize expressions that were *never* seen at training time; e.g. the input video never contained a frame where both eyes were closed and the actor had a smiling expression; see Figure 1 (green box).

Contributions. To summarize, our CoNeRF method¹:

- provides *direct*, *intuitive*, and *fine-grained* control over 3D neural representations encoded as NeRF;
- achieves this via *few-shot* supervision, e.g., just a handful of annotations in the form of attribute values and corresponding 2D mask are needed for a one minute video;
- while inspired by domain-specific facial animation research [46], it provides a *domain-agnostic* technique.

2. Related works

Neural Radiance Fields [30] provide high-quality renderings of scenes from novel views with just a few exemplar images captured by a handheld device. Various extensions have been suggested to date. These include ones that focus on improving the quality of results [28, 35, 36, 50], ones that allow a single model to be used for multiple scenes [40, 44], and some considering controllability of the rendering output at a coarse level [14, 25, 47–49, 53], as we detail next.

¹Code and dataset are released [here](#).

In more detail, existing works enable only compositional control of object location [48, 49], and recent extensions also allow for finer-grain reproduction of global illumination effects [14]. NeRFactor [53] shows one can model albedos and BRDFs, and shadows, which can be used to, e.g., edit material, but the manipulation they support is limited to what is modeled through the rendering equation. CodeNeRF [18] and EditNeRF [25] showed that one can edit NeRF models by modifying the shape and appearance encoding, but they require a curated dataset of objects viewed under different views and colors. HyperNeRF [36], on the other hand can adapt to unseen changes specific to the scene, but learns an arbitrary attribute (ambient) space that cannot be supervised, and, as we show in Section 4, cannot be easily related to specific local attribute within the scene for controllability.

Explicit supervision. One can also condition NeRF representations [12] with face attribute predicted by pre-trained face tracking networks, such as Face2Face [42]. Similarly, for human bodies, A-NeRF [41] and NARF [33] use the SMPL [26] model to generate interpretable pose parameters, and Neural Actor [24] further includes normal and texture maps for more detailed rendering. While these models result in controllable NeRF, they are limited to domain-specific control and the availability of a heavily engineered control model.

Controllable neural implicit. Controllability of neural 3D *implicit* representations has also been addressed by the research community. Many works have limited focus on learning *human* neural implicit representations while enabling the control via SMPL parameters [26], or linear blend skinning weights [5, 10, 15, 27, 29, 38, 54, 55]. Some initial attempts at learned disentangled of shape and poses have also been made in A-SDF [31], allowing behavior control of the output geometry (e.g. doors open vs. closed) while maintaining the general shape. However, the approach is limited to controlling SE(3) articulation of objects, and requires dense 3D supervision.

2.1. Neural Radiance Field (NeRF)

For completeness, we briefly discuss NeRF before diving into the details of our method. A Neural Radiance Field captures a volumetric representation of a specific scene within the weights of a neural network. As input, it receives a sample position \mathbf{x} and a view direction \mathbf{v} and outputs the density of the scene σ at position \mathbf{x} as well as the color \mathbf{c} at position \mathbf{x} as seen from view direction \mathbf{v} . One then renders image pixels \mathbf{C} via volume rendering [19]. In more detail, \mathbf{x} is defined by observing rays $\mathbf{r}(t)$ as $\mathbf{x} = \mathbf{r}(t)$, where t parameterizes at which point of the ray you are computing for. One then renders the color of each pixel $\mathbf{C}(\mathbf{r})$ by computing

$$\mathbf{C}(\mathbf{r}) = \int_{t_n}^{t_f} T(t) \sigma(\mathbf{r}(t)) \mathbf{c}(\mathbf{r}(t), \mathbf{v}) dt, \quad (1)$$

where \mathbf{v} is the viewing angle of the ray \mathbf{r} , t_n and t_f are the near and far planes of the rendering volume, and

$$T(t) = \exp\left(-\int_{t_n}^t \sigma(\mathbf{r}(s)) ds\right), \quad (2)$$

is the accumulated transmittance. Integration in (1) is typically done via numerical integration [30].

2.2. HyperNeRF

Note that in its original formulation (1) is only able to model *static* scenes. Various recent works [35, 36, 43] have been proposed to explicitly account for possible appearance changes in a scene (for example, temporal changes in a video). To achieve this, they introduce the notion of *canonical hyperspace* – more formally given a 3D query point \mathbf{x} and the collection θ of all parameters that describe the model, they define:

$$\mathcal{K}(\mathbf{x}) \equiv \mathcal{K}(\mathbf{x}; \beta, \theta), \quad \text{Canonicalizer} \quad (3)$$

$$\beta(\mathbf{x}) \equiv \mathcal{H}(\mathbf{x}; \beta, \theta), \quad \text{Hyper Map} \quad (4)$$

$$\mathbf{c}(\mathbf{x}), \sigma(\mathbf{x}) = \mathcal{R}(\mathcal{K}(\mathbf{x}), \beta(\mathbf{x}); \theta). \quad \text{Hyper NeRF} \quad (5)$$

where the location is canonicalized via a canonicalizer \mathcal{K} , and the appearances, represented by β , are mapped to a hyperspace via \mathcal{H} , which are then utilized by another neural network \mathcal{R} to retrieve the color \mathbf{c} and the density σ at the query location. Note throughout this paper we denote β to indicate a latent code, while $\beta(\mathbf{x})$ to indicate the corresponding field generated by the hypermap lifting. With this latent lifting, these methods render the scene via Eq. (1). Note that the original NeRF model can be thought of the case where \mathcal{K} and \mathcal{H} are identity mappings.

3. Controllable NeRF (CoNeRF)

Given a collection of C color images $\{\mathbf{C}_c\} \in [0, 1]^{W \times H \times 3}$, we train our controllable neural radiance field model by an auto-decoding optimization [34] whose losses can be grouped into two main subsets:

$$\arg \min_{\theta=\theta, \{\beta_c\}} \underbrace{\mathcal{L}_{\text{rep}}(\theta; \{\mathbf{C}_c\})}_{\text{Section 3.1}} + \underbrace{\mathcal{L}_{\text{ctrl}}(\theta; \{\mathbf{M}_{c,a}^{\text{gt}}, \{\alpha_{c,a}^{\text{gt}}\})}_{\text{Section 3.2}}. \quad (6)$$

The first group consists of the classical HyperNeRF [36] auto-decoder losses, attempting to optimize neural network parameters θ jointly with latent codes $\{\beta_c\}$ to reproduce the corresponding input images $\{\mathbf{C}_c\}$:

$$\mathcal{L}_{\text{rep}}(\cdot) = \mathcal{L}_{\text{recon}}(\theta, \{\beta_c\}; \{\mathbf{C}_c\}) + \mathcal{L}_{\text{enc}}(\{\beta_c\}). \quad (7)$$

The latter allow us to inject *explicit control* into the representation, and are our core contribution:

$$\mathcal{L}_{\text{ctrl}}(\cdot) = \mathcal{L}_{\text{mask}}(\theta, \{\beta_c\}; \{\mathbf{M}_{c,a}^{\text{gt}}\}) \quad \text{g.t. masks} \quad (8)$$

$$+ \mathcal{L}_{\text{attr}}(\theta, \{\beta_c\}; \{\alpha_{c,a}^{\text{gt}}\}). \quad \text{g.t. attributes} \quad (9)$$

As mentioned earlier in Section 1, we aim for a neural 3D appearance model that is controlled by a collection of attributes $\alpha = \{\alpha_a\}$, and we expect each image to be a manifestation of a different value of attributes, that is, each image \mathbf{C}_c , and hence each latent code β_c , will have a corresponding attribute α_c . The learnable connection between latent codes β and the attributes α , which we represent via regressors, is detailed in Section 3.3.

3.1. Reconstruction losses

The primary loss guiding the training of the NeRF model is the reconstruction loss, which simply aims to reconstruct observations $\{\mathbf{C}_c\}$. As in other neural radiance field models [28, 30, 35, 36] we simply minimize the L2 photometric reconstruction error with respect to ground truth images:

$$\mathcal{L}_{\text{recon}}(\cdot) = \sum_c \mathbb{E}_{\mathbf{r} \sim \mathbf{C}_c} \left[\|\mathbf{C}(\mathbf{r}; \beta_c, \theta) - \mathbf{C}^{\text{gt}}(\mathbf{r})\|_2^2 \right]. \quad (10)$$

As is typical in auto-decoders, and following [34], we impose a zero-mean Gaussian prior on the latent codes $\{\beta_c\}$:

$$\mathcal{L}_{\text{enc}}(\cdot) = \sum_c \|\beta_c\|_2^2. \quad (11)$$

3.2. Control losses

The user defines a *discrete* set of A number of attributes that they seek to control, that are *sparsely* supervised across frames—we only supervise attributes *when* we have an annotation, and let others be discovered on their own throughout the training process, as guided by (7). More specifically, for a particular image \mathbf{C}_c , and a particular attribute α_a , the user specifies the quantities:

- $\alpha_{c,a} \in [-1, 1]$: specifying the value for the a -th attribute in the c -th image; see the *sliders* in Figure 1;
- $\mathbf{M}_{c,a} \in [0, 1]^{W \times H}$: roughly specifying the image region that is controlled by the a -th attribute in the c -th image; see the *masks* in Figure 1.

To formalize sparse supervision, we employ an indicator function $\delta_{c,a}$, where $\delta_{c,a} = 1$ if an annotation for attribute a for image c is provided, otherwise $\delta_{c,a} = 0$. We then write the loss for *attribute* supervision as:

$$\mathcal{L}_{\text{attr}}(\cdot) = \sum_c \sum_a \delta_{c,a} |\alpha_{c,a} - \alpha_{c,a}^{\text{gt}}|^2. \quad (12)$$

For the mask few-shot supervision, we employ the volume rendering in (20) to project the 3D volumetric neural

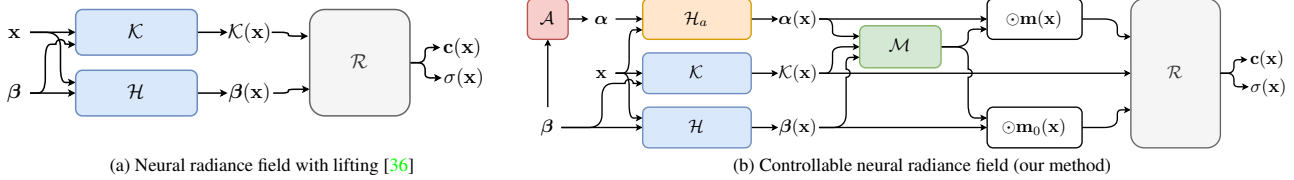


Figure 2. **Framework** – We depict in (a) the HyperNeRF [36] formulation, and (b) our Controllable-NeRF (CoNeRF). In (a), both point coordinates \mathbf{x} and latent representation β are respectively processed by a canonicalizer \mathcal{K} and a hyper map \mathcal{H} , which are then turned into radiance and density field values by \mathcal{R} . In (b), we introduce regressors \mathcal{A} and \mathcal{M} that regress the attribute and the corresponding mask that enable few-shot attribute-based control of the NeRF model. See Section 3.3 for details.

mask field $\mathbf{m}_a(\mathbf{x})$ into image space, and then supervise it as:

$$\mathcal{L}_{\text{mask}}(\cdot) = \sum_{c,a} \delta_{c,a} \mathbb{E}_{\mathbf{r}} [\text{CE}(\mathbf{M}(\mathbf{r}; \beta_c, \theta), \mathbf{M}_{c,a}^{\text{gt}}(\mathbf{r}))], \quad (13)$$

where $\text{CE}(\cdot, \cdot)$ denotes cross entropy, and the field $\sigma(\mathbf{x})$ in (20) is learned by minimizing (10). Importantly, as we do not wish for (13) to interfere with the training of the underlying 3D representation learned through (10), we *stop gradients* in (13) w.r.t. $\sigma(\mathbf{x})$. Furthermore, in practice, because the attribute mask vs. background distribution can be highly imbalanced depending on which attribute the user is trying to control (e.g. an eye only covers a very small portion of an image), we employ a *focal loss* [23] in place of the standard cross entropy loss.

3.3. Controlling and rendering images

In what follows, we drop the image subscript c to simplify notation without any loss of generality. Given a B -dimensional latent code β representing the 3D scene behind an image, we derive a mapping to our A attributes via a neural map \mathcal{A} with learnable parameters θ :

$$\{\alpha_a\} = \mathcal{A}(\beta; \theta), \quad \mathcal{A}: \mathbb{R}^B \rightarrow [0, 1]^A, \quad (14)$$

where these correspond to the *sliders* in Figure 1. In the same spirit of (4), to allow for complex topological changes that may not be represented by the change in a single scalar value alone, we lift the attributes to a hyperspace. In addition, since each attribute governs different aspects of the scene, we employ *per-attribute* learnable hypermaps $\{\mathcal{H}_a\}$, which we write:

$$\alpha_a(\mathbf{x}) = \mathcal{H}_a(\mathbf{x}, \alpha_a; \theta) \quad \mathcal{H}_a: \mathbb{R}^3 \times \mathbb{R} \rightarrow \mathbb{R}^d. \quad (15)$$

Note that while α_a is a scalar *value*, $\alpha_a(\mathbf{x})$ is a *field* that can be queried at any point \mathbf{x} in space. These fields are concatenated to form $\alpha(\mathbf{x}) = \{\alpha_a(\mathbf{x})\}$.

We then provide all this information to generate an *attribute masking field* via a network $\mathcal{M}(\cdot; \theta)$. This field determines which attribute *attends* to which position in space \mathbf{x} :

$$\mathbf{m}_0(\mathbf{x}) \oplus \mathbf{m}(\mathbf{x}) = \mathcal{M}(\mathcal{K}(\mathbf{x}), \beta(\mathbf{x}), \alpha(\mathbf{x}); \theta), \quad (16)$$

$$\mathcal{M}: \mathbb{R}^3 \times \mathbb{R}^B \times \mathbb{R}^{A \times d} \rightarrow \mathbb{R}_+^{A+1}, \quad (17)$$

where \oplus is a concatenation operator, $\mathbf{m}(\mathbf{x}) = \{\mathbf{m}_a(\mathbf{x})\}$, and the additional mask $\mathbf{m}_0(\mathbf{x})$ denotes space that is not affected by *any* attribute. Note that because the mask location should be affected by both the particular attribute of interest (e.g., the selected eye status) and the global appearance of the scene (e.g., head movement), \mathcal{M} takes both $\beta(\mathbf{x})$ and $\alpha(\mathbf{x})$ as input in addition to $\mathcal{K}(\mathbf{x})$. In addition, because the mask is modeling the attention related to attributes, collectively, these masks satisfy the partition of unity property:

$$\mathbf{m}_0(\mathbf{x}) + \sum_a [\mathbf{m}_a(\mathbf{x})] = 1 \quad \forall \mathbf{x} \in \mathbb{R}^3. \quad (18)$$

Finally, in a similar spirit to (5), all of this information is processed by a neural network that produces the desired radiance and density fields used in volume rendering:

$$\left. \begin{array}{l} \mathbf{c}(\mathbf{x}) \\ \sigma(\mathbf{x}) \end{array} \right\} = \mathcal{R}(\mathcal{K}(\mathbf{x}), \underbrace{\mathbf{m}(\mathbf{x}) \odot \alpha(\mathbf{x})}_{\text{attribute controls}}, \underbrace{\mathbf{m}_0(\mathbf{x}) \cdot \beta(\mathbf{x})}_{\text{everything else}}; \theta). \quad (19)$$

In particular, note that $\mathbf{m}(\mathbf{x})=0$ implies $\mathbf{m}_0(\mathbf{x})=1$, hence our solution has the capability of reverting to classical HyperNeRF (5), where all change in the scene is globally encoded in $\beta(\mathbf{x})$. Finally, these fields can be used to render the mask in image space, following a process analogous to volume rendering of radiance:

$$\mathbf{M}(\mathbf{r}; \theta) = \int_{t_n}^{t_f} T(t) \cdot \sigma(\mathbf{r}(t)) \cdot [\mathbf{m}_0(\mathbf{r}(t)) \oplus \mathbf{m}(\mathbf{r}(t))] dt. \quad (20)$$

We depict our inference flow in Figure 2 (b).

3.4. Implementation details

We implement our method for NeRF based on the JAX [8] implementation of HyperNeRF [36]. We use both the scheduled windowed positional encoding and weight initialization of [35], as well as the coarse-to-fine training strategy [36].

Besides the newly added networks, we follow the same architecture as HyperNeRF. For the attribute network \mathcal{A} we use a six-layer multi-layer perceptron (MLP) with 32 neurons at each layer, with a skip connection at the fifth layer, following [35, 36]. For the lifting network \mathcal{H}_a , we use the

same architecture as \mathcal{H} , except for the input and output dimension sizes. For the masking network \mathcal{M} we use a four-layer MLP with 128 neurons at each layer, followed by an additional 64 neuron layer with a skip connection. The network \mathcal{R} also shares the same architecture as HyperNeRF, but with a different input dimension size to accommodate for the changes our method introduces.

2D implementation. To show that our idea is not limited to neural radiance fields, we also test a 2D version of our framework that can be used to directly represent images, without going through volume rendering. We use the same architecture and training procedure as in the NeRF case, with the exception that we do not predict the density σ , and we also do not have the notion of depth—each ray is directly the pixel. We center crop each video and resize each frame to be 128×128 .

Hyperparameters. We train all our NeRF models with 480×270 images and with 128 samples per ray. We train for 250k iterations with a batch size of 512 rays. During training, we maintain that 10% of rays are sampled from annotated images. We set $\mathcal{L}_{\text{attr}} = 10^{-1}$, $\mathcal{L}_{\text{mask}} = 10^{-2}$ and $\mathcal{L}_{\text{enc}} = 10^{-4}$. For the number of hyper dimensions we set $d = 8$. For the 2D implementation experiments, we sample 64 random images from the scene and further subsample 1024 pixels from each of them. For all experiments we use Adam [20] with learning rate 10^{-4} exponentially decaying to 10^{-5} in 250k iterations. We provide additional details in the supplementary material. Training a single model takes around 12 hours on an NVIDIA V100 GPU.

4. Results

4.1. Datasets and baselines

We evaluate our method on two datasets: real video sequences captured with a smartphone (*real dataset*) and synthetically rendered sequences (*synthetic dataset*). Here we introduce those datasets and the baselines for our approach.

Real dataset. Each of the seven real sequences is 1 minute long and was captured either with a Google Pixel 3a or an Apple iPhone 13 Pro. Four of them consists of people performing different facial expressions including smiling, frowning, closing or opening eyes, and opening mouth. For the other three, we captured a toy car changing its shape (*a.k.a.* Transformer), a single metronome, and two metronomes beating with different rates. For one of the four videos depicting people, to use it for the 2D implementation case, we captured it with a static camera that shows a frontal view of the person. All other sequences feature camera motions showing front and sides of the object in the center of the scene. For videos with human subjects, the subjects signed a participant consent form, which was approved by a research ethics board. We informed the participants that

their data will be altered with our method.

We extract frames at 15 FPS which gives approximately 900 frames per capture. Because novel attribute synthesis via user control on real scenes does not have a ground truth view—we aim to create scenes with unseen attribute combinations—the benefit of our method is best seen qualitatively. Nonetheless, to quantitatively evaluate the rendering quality, we interpolate between two frames and evaluate its quality. In more detail, to minimize the chance of the dynamic nature of the scene interfering with this assessment, we use every other frame as a test frame for the interpolation task.

For all human videos, we define three attributes—one for the status of each of the two eyes, and one for the mouth. We annotate only six frames per video in this case, specifically the frames that contain the extremes of each attribute (*e.g.*, left eye fully open). For the toy car, we set the shape of the toy car to be an attribute, and annotate two extremes from two different view points—when the toy is in robot-mode and when it is in car-mode from its left and right side. For the metronomes, we consider the state of the pendulum to be the attribute and annotate the two frames with the two extremes for the single metronome case, and seven frames for the two metronome case as the pendulums of the two metronomes are often close to each other and required special annotations for these close-up cases; see Figure 3.

Synthetic dataset. Since the lack of ground-truth data renders measuring the quality of novel attribute synthesis infeasible in practice, we leverage Kubric software [13] to generate synthetic dataset, where we know exactly the state of each object in the scene. We create a simple scene where three 3D objects, the teapot [3], the Stanford bunny [1], and Suzanne [2], are placed within the scene and are rendered with varying surface colors, which are our attributes; see Figure 5. We generate 900 frames for training and 900 frames for testing. To ensure that the attribute combination during training is not seen in the test scene, we set the attributes to be synchronized for the training split, and desynchronized for the test split. We further render the test split from different camera positions than the training split to account for novel views. We randomly sample 5% of the frames with a given attribute for each object to be set as the ground-truth attribute. During validation, we use attribute values directly to predict the image.

Baselines. To evaluate the reconstruction quality of our method, CoNeRF, we compare it with four different baselines: ① standard NeRF [30]; ② NeRF+Latent, a simple extension to NeRF where we concatenate each coordinate \mathbf{x} with a learnable latent code β to support appearance changes of the scene; ③ Nerfies [35]; and ④ HyperNeRF² [36]. Additionally, as existing methods do not sup-

²We use the version with dynamic plane slicing as it consistently out-

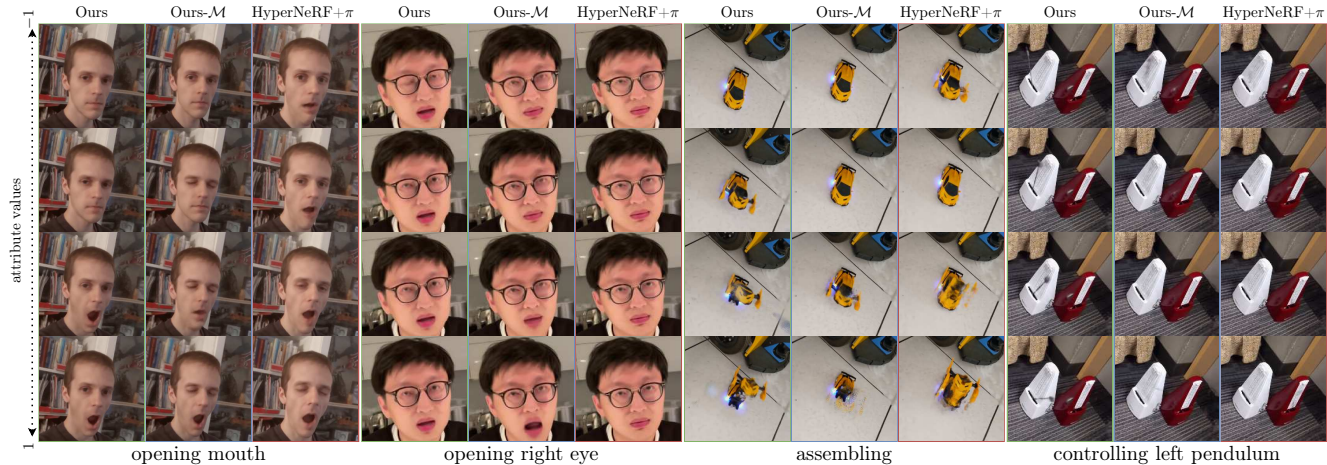


Figure 3. **Novel view and novel attribute synthesis on real data** – We synthesize scenes from a novel view and with a novel attribute combination, not seen during training. A naive extension of HyperNeRF, HyperNeRF+ π fails to disentangle attributes and results in a modification of the scene irrespectively of attribute meaning *e.g.*, opening mouth results in closing eyes at the same time. Ours- \mathcal{M} improves the results, but does not disentangles the attribute space, as successfully done by our complete method. The differences between these methods can even lead to complete failure cases, as shown in the metronome and the toy car case.

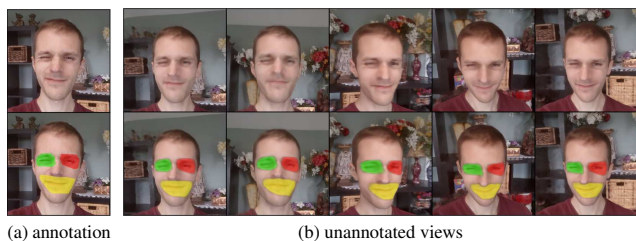


Figure 4. **Annotation example** – We provide only a rough annotation for each attribute, which is enough for the method to discover the mask for each attribute across all views automatically. Bottom row shows masks overlaid on the image.

port attribute-based control with a few-shot supervision, we create another baseline ⑤ by extending HyperNeRF with a simple linear regressor π that regresses β_c given α_c . We call this baseline HyperNeRF+ π . To further show the importance of masking, we also compare our approach against a stripped-down version of our method, Ours- \mathcal{M} , where we disable the part of our pipeline responsible for masking. All baselines that utilize annotations were trained with the same sparse labels as our method.

4.2. Comparison with the baselines

Qualitative highlights. We first show qualitative examples of novel attribute and view synthesis on the real dataset in Figure 3. Our method allows for controlling the selected attribute without changing other aspects of the image—our control is disentangled. This disentanglement allows our method to generate images with attribute combinations that were not seen at training time. On the contrary, as

there is no incentive for the learned embeddings of Hy-

Method	PSNR \uparrow	MS-SSIM \uparrow	LPIPS \downarrow
HyperNeRF+ π	25.963	0.854	0.158
Ours-\mathcal{M}	27.868	0.898	0.155
Ours	32.394	0.972	0.139

Table 1. **Novel view and novel attributes results** – We report average PSNR, MS-SSIM, and LPIPS values for novel view and novel attribute synthesis on synthetic data. Our method gives the best results.

perNeRF to be disentangled, the simple regression strategy of HyperNeRF+ π results in entangled control, where when one tries to close/open the mouth it ends up affecting the eyes. The same phenomenon happens also for Ours- \mathcal{M} . Moreover, due to the complexity of motions in the scene, HyperNeRF+ π fails completely to render novel views of the toy car, whereas our method, with only four annotated frames, successfully provides both controllability and high-quality renderings. Please also see [Supplementary Material](#) for more qualitative results, including a video demonstration.

Note that in all of these sequences, we provide highly sparse annotations and yet our method learns how each attribute should influence the appearance of the scene. In Figure 4, we show an example annotation and how the method finds the mask for unannotated views.

Quantitative results on synthetic dataset. To complete the qualitative evaluation of our method, we provide results using synthetic dataset with available ground truth. We measure Peak Signal-to-Noise Ratio (PSNR), Multi-scale Structural Similarity (MS-SSIM) [45], and Learned Perceptual Image Patch Similarity (LPIPS) [51] and report them

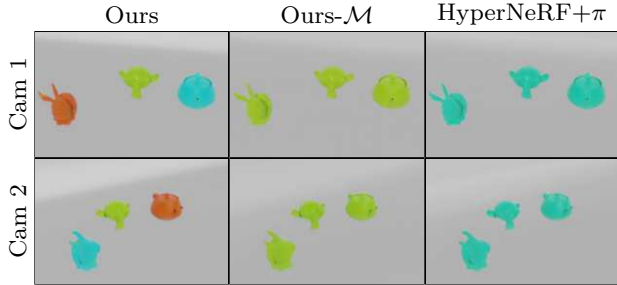


Figure 5. **Novel view and novel attribute synthesis on synthetic data** – We show examples of novel view and novel attribute synthesis on synthetic data. The scene is composed of three objects, where the color of each object is their attribute. Our method provides control over the color of each object independently, whereas both HyperNeRF+ π and Ours- \mathcal{M} fail to deliver controllability and results in all three objects having the same attribute in the rendered scene.

Method	PSNR \uparrow	MS-SSIM \uparrow	LPIPS \downarrow
NeRF	28.795	0.951	0.210
NeRF + Latent [30]	32.653	0.981	0.182
NeRFies [35]	32.274	0.981	0.180
HyperNeRF [36]	32.520	0.981	0.169
Ours-\mathcal{M}	32.061	0.979	0.167
Ours	32.342	0.981	0.168

Table 2. **Quantitative results (interpolation)** – We report results in terms of PSNR, MS-SSIM, and LPIPS for the interpolation task. These results are obtained for interpolated view synthesis only, not for novel attribute rendering. Our method provides similar performance in terms of rendering quality, but with controllability.

in Table 1. With only 5% of the annotations, our method provides the best novel-view and novel-attribute synthesis results, as reconfirmed by the qualitative examples in Figure 5. As shown, neither HyperNeRF+ π nor Ours- \mathcal{M} is able to provide good results in this case, as without disentangled control of each attribute, the novel attribute and view settings of each test frame cannot be synthesized properly.

Interpolation task. To further verify that our rendering quality does not degrade with the introduction of controllability, we evaluate our method on a frame interpolation task without any attribute control. Unsurprisingly, as shown in Table 2, all methods that support dynamic scenes work similarly, including ours for interpolation. Note that for the interpolation task, we interpolate every other frame, in order to minimize the chance of attributes affecting the evaluation. Here, we are purely interested in the rendering quality from a novel view.

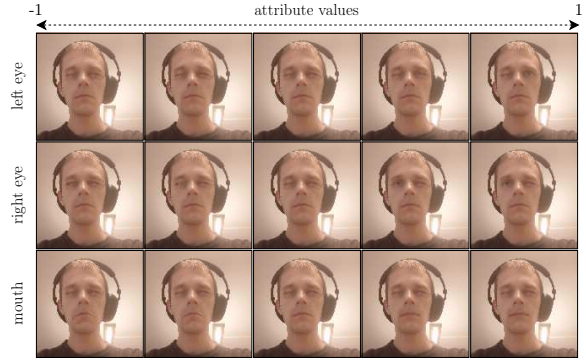


Figure 6. **2D image generation example** – Our framework also generalizes to direct generation of 2D images. Here we show novel attribute synthesis for a webcam video of a person making expressions. Each individual part of the scene is correctly controlled according to the attribute values.

Model	Real (interpolation)			Synthetic (novel view & attr.)		
	PSNR \uparrow	MS-SSIM \uparrow	LPIPS \downarrow	PSNR \uparrow	MS-SSIM \uparrow	LPIPS \downarrow
Base ($\mathcal{L}_{\text{recon}}$)	32.457	0.981	0.168	24.407	0.718	0.173
+ \mathcal{L}_{enc}	32.478	0.982	0.167	27.018	0.871	0.164
+ $\mathcal{L}_{\text{enc}} + \mathcal{L}_{\text{attr}}$	32.254	0.981	0.167	27.322	0.873	0.147
+ $\mathcal{L}_{\text{enc}} + \mathcal{L}_{\text{attr}} + \mathcal{L}_{\text{mask}}$	32.342	0.981	0.168	32.394	0.972	0.139

Table 3. **Effect of loss functions** – We report the rendering quality of our method as we procedurally introduce the loss terms. For controlled rendering with novel views and attributes (synthetic data), each loss term adds to the rendering quality, with the $\mathcal{L}_{\text{mask}}$ being critical. For the novel view rendering on real data, addition of loss functions for controllability do not have a significant effect on the rendering quality—they do no harm.

4.3. Direct 2D rendering

To verify how our approach generalizes beyond NeRF models and volume rendering, we apply our method to videos taken from a single view point, creating a 2D rendering task. We show in Figure 6 a proof-of-concept for employing our approach outside of NeRF applications to allow controllable neural generative models.

4.4. Ablation study

Loss functions. In Table 3, we show how each loss term affects the network’s performance, contributing to performance improvements. When rendering novel views with novel attributes, the full formulation is a must, as without all loss terms the performance drops significantly—for example, results without $\mathcal{L}_{\text{mask}}$ is similar to Ours- \mathcal{M} results in Table 1 and Figure 5. In the case of the interpolation task, the additional loss functions for controllability have no significant effect on the rendering quality. In other words, our controllability losses **do not interfere** with the rendering quality, other than imbuing the framework with controllability.

Quality of few shot supervision. We test how sensitive our method is against the quality of annotation supervision. In

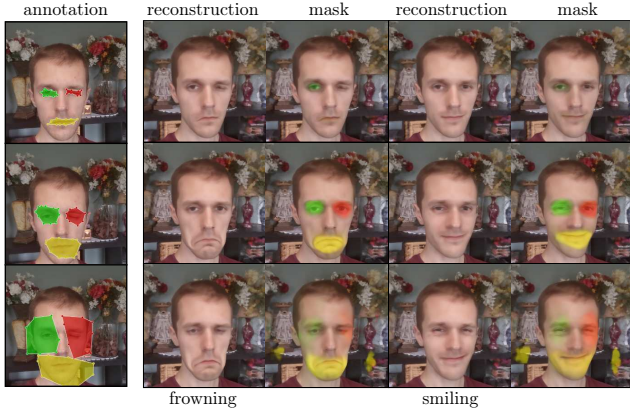


Figure 7. **Effect of annotation quality** – Our method is moderately robust to the quality of annotations. We visualize the results for two expressions: frowning and smiling, while keeping both eyes in a neutral position. Even with wildly varying annotations as shown, the reconstructions are reasonably controlled, with the exception of the top row, where we show a case where the annotations is too restrictive, resulting in the annotation being ignored for one eye. We show in bottom row also an interesting case, where the mask is large enough to start capturing the correlation among mouth expressions and the eye.

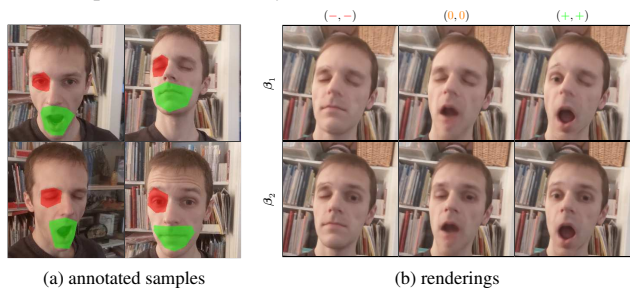


Figure 8. **Example with unannotated attributes** – We show an example of how our method performs when a part of the image changes appearance, but is not annotated. With the annotations in (a), we synthesize the scene with novel view and attributes in (b), where the two rows are with different β configurations. We denote the attribute configuration on the top of each column in (b). As shown, the change that is not annotated is simply encoded in the per-image encoding β .

Figure 7 we demonstrate how each annotation leads to the final rendering quality. Our framework is robust to a moderate degree to the inaccuracies in the annotations. However, when they are too restrictive, the mask may collapse, as shown on the top row. Too large of a mask could also lead to moderate entanglement of attributes, as shown in the bottom row. Still, in all cases, our method provides a reasonable control over what is annotated.

Unannotated attributes. A natural question to ask is then what happens with the unannotated changes that may exist in the scene. In Figure 8 we show how the method performs when annotating only parts of the appearance change within the scene. The unannotated changes of the scene get encoded as β , as in the case of HyperNeRF [36].

5. Conclusions

We have introduced CoNeRF, an intuitive controllable NeRF model that can be trained with few-shot annotations in the form of attribute masks. The core contribution of our method is that we represent attributes as localized masks, which are then treated as latent variables within the framework. To do so we regress the attribute and their corresponding masks with neural networks. This leads to a few-shot learning setup, where the network learns to regress provided annotations, and if they are not provided for a given image, proper attributes and masked are discovered throughout training automatically. We have shown that our method allows users to easily annotate what to control and how, within a single video simply by annotating a few frames, which then allows rendering of the scene from novel views and with novel attributes, at high quality.

Limitations. While our method delivers controllability to NeRF models, there is room for improvement. First, our disentanglement of attribute strictly relies on the locality assumption—if multiple attributes act on a single pixel, our method is likely to have entangled outcomes when rendering with different attributes. An interesting direction would therefore be to incorporate manifold disentanglement approaches [22, 52] to our method. Second, while very few, we still require sparse annotations. Unsupervised discovery of controllable attributes, for example as in [21], in a scene remains yet to be explored. Lastly, we resort to user intuition on which frames should be annotated—we heuristically choose frames with extreme attributes (*e.g.*, mouth fully open). While this is a valid strategy, an interesting direction for future research would be to employ active learning techniques for this purpose [6, 37]

We further discuss potential societal impact of our work in the Supplementary Material.

6. Acknowledgements

We thank Thabo Beeler, JP Lewis, and Mark J. Matthews for their fruitful discussions, and Daniel Rebaín for helping with processing the synthetic dataset. The work was partly supported by National Sciences and Engineering Research Council of Canada (NSERC), Compute Canada, and Microsoft Mixed Reality & AI Lab. This research was funded by Foundation for Polish Science (grant no POIR.04.04.00-00-14DE/18-00 carried out within the Team-Net program co-financed by the European Union under the European Regional Development Fund), National Science Centre, Poland (grant no 2020/39/B/ST6/01511), and by Microsoft Research through EMEA PhD Scholarship Programme. The authors have applied a CC BY license to any Author Accepted Manuscript (AAM) version arising from this submission, in accordance with the grants’ open access conditions.

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