Guided Co-Modulated GAN for 360° Field of View Extrapolation

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https://lvsn.github.io/ImmerseGAN/

Abstract

We propose a method to extrapolate a 360° field of view from a single image that allows for user-controlled synthesis of the out-painted content. To do so, we propose improvements to an existing GAN-based in-painting architecture for out-painting panoramic image representation. Our method obtains state-of-the-art results and outperforms previous methods on standard image quality metrics. To allow controlled synthesis of out-painting, we introduce a novel guided co-modulation framework, which drives the image generation process with a common pretrained discriminative model. Doing so maintains the high visual quality of generated panoramas while enabling user-controlled semantic content in the extrapolated field of view. We demonstrate the state-of-the-art results of our method on field of view extrapolation both qualitatively and quantitatively, providing thorough analysis of our novel editing capabilities. Finally, we demonstrate that our approach benefits the photorealistic virtual insertion of highly glossy objects in photographs.

1. Introduction

Photographs show a glimpse of reality captured when the shutter is pressed: they are but a small window on a full 360° scene. Despite the limits of cameras, one can easily imagine the full scene in which the image was captured: surely there is a large tree casting this shadow on the lawn; undoubtedly there must be other vehicles passing by this busy street. In computer vision, extrapolating content outside the frame boundaries is known as image out-painting.

While image synthesis methods [16, 15, 5] have long been used as a solution to this problem, more recently learning-based methods which leverage learned priors for this task [39] have been shown to yield more promising results. For example, methods have been trained to generate images that would likely arise if one were to continuously pan (i.e., translate) the camera [10, 40, 69, 41]. These methods expand the field of view (FOV) solely in front of the camera assuming the scene is a planar grid.

We instead consider the case of generating the entire 360° around the camera, i.e., what would happen if one would rotate the camera about its center of projection. In other words, we wish to extrapolate the FOV of the camera to span a sphere around the camera. In the literature, generative adversarial networks have emerged as the method of choice for image generation and extrapolation [56, 57]. More recently, Hara et al. [25] explicitly enforce symmetries in FOV extrapolation. In parallel, CoModGAN [73] proposed a method for conditioning a StyleGAN2 generator [35] and demonstrated that impressive in-painting results can be achieved even when large portions of the image are masked out.

In this paper, we present an approach which leverages the CoModGAN architecture and makes it suitable to the

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problem of FOV extrapolation, which we frame as an image out-painting task. We show that our proposed changes are critical to achieve state-of-the-art results in this context. Because it provides an immersive view of the entire 360° from an image, we name our approach ImmerseGAN. While this technique generates high quality panoramas, it allows for very limited editing capabilities. Indeed, a user can generate new out-painting results by sampling different style vectors (i.e., running the mapping network on different random inputs), but they offer no explicit way of controlling the output since they are only conditioned on the input image.

Therefore, we also present an approach that enables class-driven editability for FOV extrapolation (fig. 1). To do so, we introduce a novel “guidance” mechanism for style co-modulation in our ImmerseGAN. Our approach relies on a discriminative network, the guide, pre-trained for scene classification on a standard labeled dataset of regular photographs [74]. Its output latent vector drives the style co-modulation mechanism in the generator. After training, a user can simply determine a target label, and the best matching latent vector for the guide is found via a simple and fast optimization procedure which does not require back-propagating through the synthesis network as is often the case. The resulting optimized latent co-modulates the style of the generator, which produces an output panorama that both 1) extrapolates a scene which semantically matches the desired label; and 2) seamlessly blends with the input image.

Our contributions are summarized as follows. First, we present an end-to-end trainable pipeline specifically tailored to the 360° FOV extrapolation task, which generates high quality panoramas from a single input image with a limited FOV. Second, we introduce a novel guided co-modulation mechanism which leverages a pre-trained discriminative model to guide the extrapolation process and allow users to determine the semantic content of the out-painted pixels. Third, we demonstrate state-of-the-art results both quantitatively and qualitatively which outperform previous methods, and provide a thorough evaluation of our novel editing capabilities. Finally, we demonstrate that our approach can be used for realistically inserting virtual objects into photos.

2. Related work

Image synthesis The generation of photorealistic synthetic images has been studied for several decades [16, 15, 5]. Recently, most image synthesis methods have been propelled by Generative Adversarial Networks (GANs) [23] due to their unparalleled capacity to model natural images. Methods evolved rapidly from the low-resolution DCGAN [49] to the high-quality results of StyleGAN and its successors [34, 35, 33], which greatly push the photorealism of synthesized images. Despite their mesmerizing results, these unconditional GANs are formulated to generate random images, with no or limited control over the generated image.

To solve this problem, conditional GANs [43] on images were proposed [30, 63]. These methods train an hourglass-like encoder-decoder architecture to translate an image from a specific domain to another, such as day to night. In contrast, Shocher et al. [53] propose to leverage VGG [55], a discriminative model trained on a large-scale dataset of images, to control the images synthesized by the generator. We draw inspiration from the latter to take advantage of transfer learning to add editing capabilities to our model.

Several methods were proposed to add editing capabilities [8, 6] to GANs, and to invert pre-trained models [66, 2, 75]. Another approach recently explored is to perform editing directly on the latent space instead of image space, see [72] for a survey. In a nutshell, these methods discover properties of the latent space of a pre-trained GAN. Work in this field has focused on uncovering semantic directions, either in a supervised [22, 31, 52] or unsupervised way [29], or on spatially editing images using GANs [76, 7, 44, 9]. We draw inspiration from these insightful ideas, and propose a method for editing the generated image that does not require a labelled dataset of panoramas while providing explicit control over the desired output (as opposed to unsupervised). Our method also does not require inversion, a process which recovers good but often imperfect reconstructions [75].

Inpainting The goal of image inpainting is to fill the gaps in a partially observed (or masked) image [16, 15, 5]. Recently, many approaches were developed to perform inpainting using GANs, for example using a patchGAN discriminator [14] or an attention mechanism [71]. The current state-of-the-art, CoModGAN [73], proposes to convert a StyleGAN generator to a conditional model using co-modulation. In our method, we propose improvements to the CoModGAN architecture to generate panoramas. Inpainting is also needed in the related task of novel view synthesis [28, 1, 47, 32], where filling disocclusions and generating new textures is necessary to produce a plausible image.

Field of View (FOV) extrapolation Similar to inpainting, FOV extrapolation can be framed as outpainting, which aims at extending the images beyond the original camera frame. Several GAN-based methods have been proposed [51], notably by extending the original image over the peripheral vision [36, 70]. Other works propose to generate realistic translations (or pans) of the camera [10, 40, 69]. These methods expand the scene on a planar grid, which allows for interesting and useful artistic effects. However, this planar grid representation cannot model the entire 360° field of view as this is represented by a sphere rather than a plane.

Many methods have tackled the full 360° FOV extrapolation. PINET [24] uses a cubemap projection to limit the amount of distortion when performing inpainting directly
on $360^\circ$ panoramas. Im2Pano3D \cite{57} estimates a plausible $360^\circ$ segmentation map from a regular image, giving hints about the content around the camera. Sumantri \textit{et al.} \cite{59} present a method to recover a $360^\circ$ panorama from four images taken uniformly along the horizon. Srinivasan \textit{et al.} \cite{58} estimate a $360^\circ$ panorama for any location of a scene using a narrow-baseline stereo image pair. Closer to our work, Akimoto \textit{et al.} \cite{3}, and Somanath and Kurz \cite{56} suggest using a GAN to generate $360^\circ$ panoramas. Hara \textit{et al.} \cite{25} go one step further and propose to leverage symmetries usually present in environments to generate a full $360^\circ$ panorama from a single image. Recently, Akimoto \textit{et al.} \cite{4} utilize a transformer-based architecture \cite{17} to predict environment maps for creating 3DCG backgrounds.

3. Method

3.1. Co-modulated GANs

Our work builds on the recently-proposed CoModGAN architecture \cite{55}, which we briefly present here for completeness and illustrate in fig. 2a. The warped image $\hat{x}$ is given as input to an encoder $E$, whose output is combined to that of the mapper $M$ via an affine transform $A$:

$$w' = A(E(\hat{x}), M(z)),$$

where $z \sim N(0, I)$ is a random noise vector, and $w'$ is the style vector modulating the synthesis network $S$. The output of $E(\hat{x})$ is provided as the input tensor to $S$.

3.2. ImmerseGAN

Although CoModGAN produces high-quality results for image completion, it is not suitable for FOV extrapolation due to two reasons. First, CoModGAN generates random masks during the training that do not represent typical scenarios of FOV extrapolation. Therefore, CoModGAN produces blurry results at test time. Second, since it is designed for inpainting in perspective images, it cannot cope with the “wrap-around” nature of panoramic images—rotating the generated panorama by $180^\circ$ about the vertical axis will reveal a strong vertical edge. Potential solutions to these artifacts have been proposed in the literature, including complex changes such as circular padding \cite{25} or sphere-projected convolutions \cite{18} (dubbed “EquiConvs”).

We introduce ImmerseGAN, which is built on the CoModGAN architecture with three modifications to address the mentioned problems. We replace random masks by generating FOV masks during training. This helps the network generate better quality results by introducing FOV biases. To address the problem of generating vertical edges, we leverage the nature of generative adversarial networks and horizontally shift the generator output before feeding it to the discriminator. This operator encourages the generator to produce panoramas with no discontinuities at the edges.

![Diagram](image)

Figure 2: Overview of our guided co-modulation method. The input image $x$ is first warped according to its (known) camera parameters to a $360^\circ$ panorama $\hat{x}$ via a (non-trainable) warp. (a) As proposed in CoModGAN \cite{55}, an encoder $E$ co-modulates (with the mapper $M$) the synthesis network $S$ according to $\hat{x}$. Here, $A$ denotes a (learnable) affine transformation. (b) In contrast, our method guides the co-modulation process with a pre-trained “Guide” model $G$, which operates directly on the input image $x$. $G$ produces a latent vector $g$ which is used for co-modulation, and which can also be run through a classification layer $c$ to produce a label map $t$. This gives the user control over the generation process by defining a new label $t$ and optimizing to determine a modified $g^*$ that modulates the synthesizer to generate the desired label (red dashed line).

Finally, we modify the architecture to yield a 2:1 aspect ratio to avoid anisotropic upsampling artifacts when mapping the output to the equirectangular representation.

3.3. Guided co-modulation

While our proposed ImmerseGAN produces state-of-the-art results for FOV extrapolation (sec. 4.2), the main limitation of this method is the lack of control over the output. Our goal is to leverage the knowledge of a “guide” network pre-trained on a large-scale scene classification task. This guide network produces two outputs: a feature vector (used to modulate our generator) and the image class (identifying the image content). For a given image at test time, we optimize the feature vector by backpropagating a user-provided desired class, as shown by the red path in fig. 2b. We repeat this operation around 2000 iterations, until convergence. We then feed this optimized feature vector to the generator.

We assume the guide network $G$ has been trained for classification, and produces an intermediate latent vector $g = G(x)$ from the input (unwarped) image $x$. $g$ is subsequently fed to a classification subnetwork, $t = c(g)$. Here, $t \in \mathbb{R}^N$ is the vector of predicted probabilities over $N$ classes. The guided co-modulated style vector $w'$ is

$$w' = A(G(x), M(z)).$$

(a) Co-modulation \cite{55} (b) Guided co-modulation
We can tune the output appearance $y$ by modifying the latent vector $g$ to represent another class by optimizing a one-hot vector $\hat{t}$ with the desired class

$$g^* = \arg \min_g \ell(c(g), \hat{t}),$$  \hspace{1cm} (3)

where $\ell$ is a binary cross-entropy loss function. A panorama, whose appearance outside the FOV of the input image should better match $\hat{t}$ is produced by replacing $g \leftarrow g^*$, i.e.,

$$w' = A(g^*, M(z)).$$  \hspace{1cm} (4)

In contrast to existing editing methods, our pipeline does not require training the guide model on the domain output by the synthesizer (panoramas), any model pre-trained on regular images can do. It also does not require any analysis of the learned latent space.

3.4. Implementation details

We assume the camera parameters to be known a priori. Other works, i.e., [27, 67] could be used to estimate them otherwise. Similar to [73], we concatenate the image’s FOV mask with the input panorama $\bar{x}$ before being fed to the network. The known pixel values in $\bar{x}$ are copied over the output $y$ before being passed to the discriminator (not shown in fig. 2). The guide network $G$ is an 18-layer ResNet [26] pre-trained on the Places365 [74] dataset. The output of the guide network, $g \in \mathbb{R}^{512}$, is produced by the penultimate layer of the ResNet, after the 1D-flatten. Please refer to supp. materials for more details regarding the network architecture.

4. Field of view extrapolation experiments

4.1. Datasets

To generate training data, we employ a similar strategy as previous works [25, 56] and extract rectified crops from a large dataset of 360° panoramas. We leverage a dataset of 250,000 (unlabelled) panoramas obtained from 360Cities\(^1\). The dataset is split into 248K/1K/1K train/validation/test subsets. When training (and for validation), random crops are computed on the fly to ensure as diverse a set as possible. For this, the parameters are sampled as $h_\theta \sim \mathcal{U}(40, 120)$ for the FOV and $\beta \sim \mathcal{N}(0, 30)$ for the elevation angle, where $\mathcal{U}$ and $\mathcal{N}$ are uniform and normal distributions respectively. After sampling, $\beta$ is clipped to $[30, 30]$. For the test set, we use a set of 1,170 panoramas balanced between outdoor and indoor scenes that are not used during the training. We extract a set of 4,680 images at fixed FOV $h_\theta \in \{40, 60, 90, 120\}$, with elevation $\beta = 0$. We also extract another set of 1,170 images, dubbed “mixed”, where the parameters are sampled randomly (according to the same distribution as above).

\(^1\)https://www.360cities.net/, acquired under proprietary license with right to publish.

| Method                  | 40°  | 60°  | 90°  | 120° | Mixed  |
|-------------------------|------|------|------|------|--------|
| pix2pixHD [63]          | 226.41 | 163.19 | 100.18 | 58.09 | 122.18 |
| Symmetry [25]-R         | 106.89 | 79.86 | 64.91 | 62.24 | 62.28  |
| Symmetry [25]-G         | 92.97  | 75.66 | 61.60 | 62.15 | 56.04  |
| CoModGAN-1x1 [73]       | 82.80  | 68.02 | 47.36 | 37.84 | 48.68  |
| CoModGAN-2x1 [73]       | 79.05 | 67.72 | 46.33 | 35.34 | 47.91  |
| ImmerseGAN (ours)       | 37.90  | 35.55 | 32.25 | 28.92 | 32.48  |
| ImmerseGAN-Guided (ours)| 37.15  | 34.65 | 32.41 | 32.97 | 35.01  |

Table 1: FID computed on the test set for various methods at varying FOVs. The 40°, 60°, 90°, and 120° columns report results on images with $\beta = 0$ and the corresponding fixed FOV. The “mixed” column represents a set of images with mixed parameters, see text for details. Each row is color-coded as best and second best.

4.2. Evaluation of field of view extrapolation

We now proceed to compare our method quantitatively and qualitatively with the state-of-the-art on our test set. First, we train a pix2pixHD [63] model on our training set. Instead of an all-black mask, we fill the background with random noise as suggested in [56], which also improved results in our experiments. To compare with the symmetry-based approach of Hara et al. [25], the authors graciously ran their code on our test set. We also train two different versions of CoModGAN [73]: an original version without any modifications (dubbed “CoModGAN-1x1”) and a modified architecture to work on 2:1 aspect ratios (“CoModGAN-2x1”). All other methods were trained on our train set (sec. 4.1) for five days on eight V100 GPUs. All methods produce outputs of $512 \times 256$ resolution, which was chosen to conduct a fair quantitative evaluation against Hara et al. [25]. However, our method can generate outputs up to $2048 \times 1024$ resolution (see supp. materials).

Comparative quantitative results are reported in tab. 1, and corresponding qualitative results in fig. 3. Results are grouped according to the test subsets (c.f. sec. 4.1). Unsurprisingly, all methods perform better when the FOV of the input image increases (the task is indeed easier since fewer pixels need to be out-painted). We note that pix2pixHD [63] results in catastrophic FIDs at $\beta < 120^\circ$, which could be partially explained by the mode collapse visible in fig. 3 where the generated panoramas all have the same specific pattern on the left. For [25], we report both their “reconstruction” and “generation” settings, denoted by the “-R” and “-G” suffixes respectively. The “generation” results being superior to “reconstruction” in tab. 1, only those results are therefore shown in fig. 3. Overall, ImmerseGAN, or its Guided version, yield the lowest FIDs throughout all test subsets. In addition, as shown in tab. 1, only changing the architecture of CoModGAN to 2:1 ratio is not enough to achieve SOTA: all of our proposed modifications are necessary. For the rest of the paper, we use CoModGAN-2x1 for the comparisons.
Figure 3: Qualitative field of view extrapolation results. Previous works [63, 25, 73] present obvious visual artifacts, including mode collapse [63], blurriness [63, 25], and semantic mismatch [63, 25]. In contrast, our ImmerseGAN enables high-quality results (penultimate column), which are preserved by our novel guided co-modulation framework (last column). The first four rows contain examples from the “fixed-fov” subset of our test set, while the last six are taken from the “mixed” subset.

Despite known limitations with FID [11], this behavior is qualitatively corroborated in fig. 3.

**CoModGAN baseline vs ImmerseGAN** To demonstrate the importance of our proposed changes in ImmerseGAN over CoModGAN [73], we present in fig. 4 a qualitative and quantitative comparison for generated panoramas after being rotated by 180° in azimuth. CoModGAN creates a visible vertical seam at the edges, which is not present with ours.

**Comparison with lighting estimation methods** Since some lighting estimation methods predict a 360° panorama for image-based lighting, we conduct a quantitative analysis to compare their performance to our proposed method. We used the Laval indoor HDR dataset [19] test set and followed the same protocols as in [56, 4]. The results are reported in tab. 2. Although all other methods have the advantage of being trained on the train set of the Laval indoor HDR dataset, our method still managed to have the best performance even against the recently published method of Akimoto et al. [4].

| Method                  | FID  |
|-------------------------|------|
| Gardner *et al.* [19]   | 197.4|
| EnvMapNet [56]          | 52.7 |
| Akimoto *et al.* [4]    | 46.15|
| ImmerseGAN (ours)       | **42.78** |

Table 2: Comparison with lighting estimation methods on the test split of Laval Indoor HDR dataset [19].
5. Guided editing experiments

5.1. Qualitative results

We now proceed to evaluate the capabilities of our novel guided co-modulation mechanism to influence the extrapolated FOV. First, several qualitative results are shown in figs. 1 and 5. Focusing on fig. 5, we observe that the generated outputs obey the semantics of the target labels while seamlessly blending in the input image. We also note that labels are responsible for specific effects, e.g., for outdoor: “sky” draws a more dramatic sky, “lawn” adds green grass, “snowfield” lets it snow, “promenade” creates a more open space with paved walk. For indoor: “entrance hall” adds doors, “corridor” elongates the scene, “artists loft” decorates with wall art, and “throne room” embellishes with banners.

5.2. Quantitative analysis

While fig. 5 showcases the high quality results obtained with the novel editing capabilities of our network, it is not clear that they should work for all combinations of image/target labels. Surely, the semantic consistency between the input image content and the target label should have an impact on the final result. For example, while it is intuitive that a “field” → “lawn” should work (first row of fig. 5), what about less meaningful mappings such as “church” → “sky” or “street” → “artist loft”? To study this, we first record the top-1 label predicted by the guide network for each image in the training set, and retain the 45 most frequent category instances. We manually assign these 45 categories to either of the generic “indoor” (22) and “outdoor” (23) sets. We then apply our guided co-modulation on 1K random images from the $h_θ = 90°$ test set (sec. 4.1) towards each of these 45 labels (generating 45K panoramas). We then extract a “backwards-looking” image that is, an image $x_{\text{back}}$ with parameters $h_θ = 90°$, $β = 0°$, azimuth angle $α = -180°$, from the generated panorama. Every pixel in this image is generated by our method, as there is no overlap between this image and the input image.

We evaluate whether the generated content is indeed of the desired label. To do so, the image $x_{\text{back}}$ is classified by $G$ to obtain class probabilities $t_{\text{back}}$. It is considered a success when the target label is contained within the top-10 (top 2.7% of labels) of $t_{\text{back}}$. As shown in tab. 3, staying within the domains (“outdoor” → “outdoor”, “indoor” → “indoor”) generates the best results. Cross-domain scenarios are more difficult because these conversions do not correspond to real-world cases. This also highlights a bias in our train set, which indeed contains more outdoor scenes than indoor, leading to better performance for outdoor (52.8%) vs. indoor (37.2%).

Fig. 6 provides a fine-grained analysis for each type of target label using the classification metric. While many labels offer good performance, others do not generate results that the guide network can successfully recognize. Those are mostly indoor labels (e.g., “ticket booth”, and “bar”), but the outdoor “boardwalk” label also yields lower performance. This label meta-analysis is particularly useful to determine which labels are likely to generate believable results ahead of time, which is confirmed by the visual results in fig. 5.

5.3. Comparison to InterFaceGAN

We compare our editing results with those obtained with InterFaceGAN [52], a StyleGAN-based face editing method which first classifies generated images using a pretrained attribute classifier, and finds semantic boundaries by fitting a linear SVM on the latent codes of images of two different classes (e.g., smile and no-smile). As mentioned in sec. 1, there exists no attribute classifier for panoramas—nor is there a labelled dataset to train one—so the method cannot be applied directly. Nevertheless, we adapt it by extracting the “backwards-looking” image $x_{\text{back}}$ (e.g. sec. 5) from a panorama generated by ImmersEGAN on a random input image and employ the guide network $G$ to obtain the label. We then fit the linear SVM in the w space (fig. 2), before the affine transformation $A$. Fig. 7 shows examples of results obtained with [52] (left) and ours (right). Results with [52] are plausible, but note how the consistency between the input crop and the extrapolated environment is weaker than with our method, resulting in strong visual artifacts (input image clearly visible in bottom-right of fig. 7) or large semantic changes (pavement turns to water in top-right of fig. 7).

6. Application: virtual object compositing

Approach One promising application of FOV extrapolation is that of virtual object compositing [13], especially when the virtual objects are highly reflective (low rough-

| Method                | 40° | 60° | 90° | 120° | Mixed |
|-----------------------|-----|-----|-----|------|-------|
| CoModGAN [73]         | 81.10 | 70.74 | 50.72 | 40.63 | 51.54 |
| ImmerseGAN (ours)     | 38.58 | 36.37 | 34.72 | 33.34 | 34.48 |

Table 3: Quantitative evaluation for guided editing, computed on an image $x_{\text{back}}$ “looking backwards”.
Figure 5: Qualitative editing results via our novel guided style co-modulation mechanism. From different input images ("Image"), an extrapolated panorama is first obtained by our network ("Image-conditioned"). A user then selects different target labels, which are used to determine the optimal vector $g^*$ for style co-modulation. Observe how the network realistically adapts to the (sometimes drastic) change of semantics between the image contents and the desired target label. The random input to the mapper $z$ is kept constant across rows to ensure the differences are only due to the guidance process.

Figure 6: Percentage of success of the guidance process as a function of the target label. From indoor/outdoor categories of input images (rows), we guide the extrapolation results to different indoor (top) and outdoor (bottom) labels and evaluate performance on classifying the extrapolated part.

Experimental results Several object insertion results are shown in figs. 1 and 8. The panoramas predicted by our method are detailed enough to enable the generation of realistic reflections off the surface of shiny objects. Also note the spatially-varying reflections that vary as a function of the position of the virtual object in the scene, thereby further increasing the realism. Our method generates sharp, realistic results even for images outside of the training domain (fig. 9), in contrast to [65] which produces blurry results for out-of-domain images. Because of its guided editing capabilities, our approach enables users to modify the appearance of the extrapolated FOV, and thus control the appearance of the virtually inserted objects (figs. 1 and 8b). See the supp. material for animations showcasing the results.
Figure 8: Virtual object insertion results. (a) Our extrapolated panoramas can be used to realistically insert shiny virtual objects, which are particularly challenging since they reflect the entire environment. (b) With our guided co-modulation technique, a user can control the semantic content of the reflections on virtual objects, by generating more dramatic clouds (↦ “sky”), suggesting a more urban environment (↦ “courtyard”), and adding more sand (↦ “beach”).

Figure 9: Comparison to Wang et al. [65] as the state-of-the-art for virtual object insertion. Our method generates sharp results, even for out-of-domain images (images from [65]).

7. Discussion

As observed in fig. 6, not all editing scenarios yield satisfying results. In particular, cross-domain translations (e.g., extrapolating an outdoor panorama from an input indoor image), yield, perhaps as expected, performance that is significantly below that of in-domain results. We also note an overall better performance for outdoor labels—achieving a better indoor/outdoor balance in the training dataset might help alleviate this. We also observe not all labels work equally well. It would be interesting to explore whether there is a relation between the semantic similarity between labels (e.g., with NLP tools [48, 45]) and the visual quality of the result. Nevertheless, the analysis performed in sec. 5 could help determining “good” labels to suggest in an interactive application, for example. Another limitation is that our proposed method allows for a global edit that modifies the entire extrapolated FOV. We are confident this framework can be extended to local edits either by leveraging the spatiality of the noise of the StyleGAN backbone or by coupling it with a local editing approach such as GAN dissection [7]. Finally, the non-Euclidean nature of the sphere manifold leads to unavoidable distortions when unfolding its surface to 2D. It would be more natural to frame 360° FOV extrapolation using spherical representations [37, 46, 18], which presents another potential exciting direction for future work.

In this work, we present a method for FOV extrapolation to a full 360° around the camera which leverages a novel guided co-modulation mechanism for controlling the appearance of the extrapolated content. The resulting spherical panoramas outperform the state-of-the-art both in terms of the standard FID metric and of visual quality. Through a detailed evaluation of our guidance-based editing mechanism, we quantify the expected visual accuracy of the generated results for a combination of input image → target label mappings, and show that high quality results can be obtained in many semantically meaningful scenarios. We demonstrate the usefulness of our approach on the application of virtual content insertion in the challenging case of highly reflective objects. We hope our approach paves the way for richer environment understanding, high-quality image editing and for helping artists realize their vision more swiftly.

Acknowledgements This work was partially supported by NSERC grant ALLRP 557208-20. We thank V. Kim, S. Amirghodsi, E. Shechtman and K. Kulkarni for helpful discussions, and everyone at UL who helped with proofreading.
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