Counterfactual Depth from a Single RGB Image

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Abstract

We describe a method that predicts, from a single RGB image, a depth map that describes the scene when a masked object is removed – we call this “counterfactual depth” that models hidden scene geometry together with the observations. Our method works for the same reason that scene completion works: the spatial structure of objects is simple. But we offer a much higher resolution representation of space than current scene completion methods, as we operate at pixel-level precision and do not rely on a voxel representation. Furthermore, we do not require RGBD inputs.

Our method uses a standard encoder-decoder architecture, and with a decoder modified to accept an object mask. We describe a small evaluation dataset that we have collected, which allows inference about what factors affect reconstruction most strongly. Using this dataset, we show that our depth predictions for masked objects are better than other baselines.

1. Introduction

People regularly reason about free space they cannot see. For example, you might reach to grasp a cup, and your fingers will fold around the back of the cup, confident that there is room. As another example, you might put a mug down on your desk behind the laptop, even though you cannot see there. While your model of this invisible space might not be precise, you have it and use it every day. When you do so, you are using “counterfactual depth” — the depth you would see if an object had been removed. This paper shows how to predict counterfactual depth from images.

This ability to “see behind” is reproduced in scene completion methods, which seek to complete voxel maps to account for the back of objects, and to infer invisible free space. But these methods produce limited resolution models of space, and require depth measurements to do so on another hand. Besides, stereo pairs provide less help to infer scene geometry behind objects, since the larger unknown depth region can’t be fully observed by small changes in camera position. While there are excellent methods for inferring depth from a single image, the resulting depth maps represent only the free space to the nearest object.

In this paper, we describe a system that can accept an image and an object mask, and produce a depth map for the scene where the masked object has been removed (Figure 1): e.g. if you mask a cup in an image of a cup on a table, our system will show you the depth behind the cup. Our method works for the same reason that scene completion works. Indoor scenes are very highly structured, and it is quite easy to come up with very good estimates of depth in unknown regions. However, image details are important: we show that our method easily outperforms Poisson smoothing of the depth map. Furthermore, our method easily outperforms the natural baseline of inpainting the image and recovering depth from the result, because inpainting often produces unnatural pixel fields.

Our approach is closely related to scene completion [42, 13], and works for the same reason that scene completion works. Scene geometries have quite simple spatially consistent structure. However, our method differs in important ways. We do not require additional depth information, and predict on RGB image only. Our system learns from images and depth maps (which are easy to acquire at a large scale), rather than from polyhedral 3D models of scenes. Rather than actively reconstructing the entire scene at lim-
2. Related Work

**Single image depth estimation** is now well established. Early approaches use biased models (e.g. boxes for rooms [16]) or aggressive smoothing (e.g. [19]). Markov random field (MRF) [38] and Conditional random field (CRF) [31] can be applied to regress image depth against monocular images. More recent approaches use deep neural networks with multi-scale predictions [11, 12], large-scale datasets [26, 2] and user interactions [37]. Stereo provides strong cues for unsupervised learning [14, 46] or semi-supervised learning with LiDAR [24]. Other approaches use sparse depth samples [32] or variational models [21]. Laina et al. [25] propose a fully convolution approach with an encoder-decoder structure, and utilize per-pixel reverse Huber loss for better predictions. Chen et al. [9] propose to learn from pixel pairs of relative depth, which is further improved with supervisions of surface normal [10]. Our approach regresses on both depth and surface normal predictions. Different from Chen et al., we pre-process the ground truth surface normal with weighted quantized vectorization to ensure a smooth prediction. Moreover, we show in experiment that, in our task, angular-based surface normal loss can help improve performance (while Chen et al. found that this is less effective).

**Depth completion** helps predict the 3D layout of a scene and the objects in a novel view. The completion can be performed on point clouds [8], RGBD sensors [43, 39, 6, 45, 30], raw depth scans [35, 13, 42] or semantic segmentations [1]. The predictions can be represented as dense depth maps [45, 30, 6], 3D meshes [35, 8], or voxels [13, 42]. Our “counterfactual depth prediction” task is challenging, because we only condition on a single RGB input and a 2D object mask only, and predict the dense depth map of the scene with the object removed – we predict the depth that can be seen and the depth that we cannot see.

We also investigate the natural baseline of removing objects from the scene – **image inpainting**. We can apply existing single image depth estimation approaches on the inpainted images, and obtain the predicted depth map with the objects removed. Image inpainting can be achieved by smoothing from unmasked neighbors [36, 7, 4], patch-based approaches [5, 15], planar structure guidance [17] or convolution neural networks [18, 44, 28, 34]. We use the method by Iizuka et al. [18], which is one of the state-of-the-art for high resolution predictions with source code available, as our image inpainting baseline.

3. Approach

Assume a single RGB image \( I \) is given. Now, for any object mask \( M_{\text{object}} \) that identifies an object in the scene, write \( M \) for the set of pixels lying on the object. We would like to predict the depth for the scene with that object removed (Figure 2). We write \( d \) for the depth field; \( d_{\text{behind}} \) for the depth predicted for pixels in \( M \) (i.e. the depth behind the object in the mask); and \( d_{\text{observe}} \) for the depth predicted for pixels out of \( M \). For example, if the scene had a cup on a desk, and the mask lay on the cup, then \( d_{\text{behind}} \) would be the desk behind the cup, \( d_{\text{observe}} \) would be the rest of the desk, and \( d_{\text{behind}} \) should be predictable because of the spatial coherence of objects.

3.1. Network architecture

Figure 2 gives an overview of our network. We choose to modify the depth predictor by Laina et al. [25], because it is fully convolutional, and can model the dense spatial relationship between \( d_{\text{behind}} \) and \( d_{\text{observe}} \). The encoder-decoder strategy of that method allows coarse-to-fine corrections of \( d_{\text{behind}} \). Our network’s input RGB image size is \( 228 \times 304 \times 3 \) (height \( \times \) width \( \times \) dimension) and the output depth map is \( 128 \times 160 \times 1 \). The encoder is based on Resnet-50, with the fully-connected layers and the top pooling layers removed. The bottleneck feature space is \( 8 \times 10 \times 1024 \). The decoder consists of four up-projection blocks and a \( 3 \times 3 \) convolution layer afterwards. We use the object mask \( M_{\text{object}} \) to guide the prediction by concatenating \( M_{\text{object}} \) to each of the input feature layers of the up-projection block. \( M_{\text{object}} \) is 0 for pixels on the object to be removed and is otherwise 1 for non-removed area. The bottleneck forces the decoder to capture long scale order in depth fields; the mask then informs the decoder where it should ignore image features and extrapolate depth. Extrapolation is helped by having an image feature encoded, because the features give some information about the likely depth behavior at the boundary of the mask, so the decoder can extrapolate into the masked region using both depth prior statistics and feature information to guide the extrapolation. This comes at the cost...
of training difficulty. The decoder has a strictly more difficult task than Laina et al.’s decoder, because it must be willing to extrapolate into any masked region supplied at run time. We also experienced with concatenating the object mask with the input RGB image as input, but observed performance degrades.

### 3.2. Network loss

Given a predicted image depth $\hat{d}$, and a ground truth depth $d$, the overall network loss for each image $I$ is:

$$L(d, \hat{d}) = w_1 L_{\text{surface}}(d, \hat{d}) + w_2 L_{\text{avg}}(d, \hat{d}) + w_3 \text{berHu}(d, \hat{d})$$

(1)

$L(d, \hat{d})$ is the weighted summation of the surface normal loss $L_{\text{surface}}$, the average image depth difference $L_{\text{avg}}$ and the pixel-wise reverse Huber (berHu) loss [33].

**Surface normal loss with weighted smoothed ground truth.** Much of the world is made of large polygons [8, 17], so that we can expect strong spatial correlations in surface normal. One can obtain small depth errors with large surface normal errors, which suggests controlling surface normal directly. We use a loss that encourages normals derived from the predicted depth to be accurate:

$$L_{\text{surface}}(d, \hat{d}) = -\sum_{p \in I} c_p \log \left( \frac{N(d_p) \cdot N'(\hat{d}_p)}{Q} \right)$$

(2)

$L_{\text{surface}}$ penalizes the average pixel-wise negative log likelihood of the angular distance between the predicted surface normal and the ground truth. $p$ denotes a pixel in $I$ positioned at $(x, y)$. $Q$ denotes the total number of pixels in $I$, and $c_p$ is the pixel-wise weight that we will explain later. $N'()$ denotes the surface normal computation which is the first-order derivatives of predicted depth.

However, computing ground truth normals $N(\cdot)$ requires care. For two adjacent pixels with only a few millimeters apart, a small error in measurement can still produce a steep change in normal direction. We apply a window-based gradient smoothing method, given known camera focal length $f_x$ and $f_y$ in $x$ and $y$ dimension respectively, computing gradients $n_p = (n_{px}, n_{py}, n_{pz})$ at pixel $p$ based on the neighboring pixels: $n_{px} = f_x \frac{1}{8} \sum_i d(x+i,y) \cdot d(x-i,y)$, $i \in \{1, 2, \ldots, 8\}$. We compute $n_{py}$ in the same way, set $n_{pz} = 1$ and normalize $n_p$ to unit 1.

We then smooth the normal spatially, using a procedure to retain sharp normal discontinuities. We quantize each ground truth normal into discrete bins. We divide the hemisphere of the normal space (assuming all pointing towards the viewpoint) into equally spanned bins of 16 latitudes and 4 azimuths. Then, we score the confidence of each bin belonging to the pixel’s normal based on the weighted average angular distance to the pixel’s $8 \times 8$ neighbors: $c_b = \frac{1}{64} \sum_q (\max(n_q \cdot n_b, 0))^\beta$. $q$ denotes a pixel in neighborhood, $n_b$ denotes candidate bin $b$’s normal. We set $\beta = 8$ to model a smooth decrease of the angle between two normal vectors going further apart. Finally, we assign the highest score to $c_p$ and its normal to $n_p$. The advantage of the weighting strategy is that for a flat ground truth region, most of the processed ground truth normal will be in the same bin, so we will recover a constant plane. Similarly, at a normal discontinuity (e.g. a ridge), one normal will dominate on one side and the other will dominate on the other, so the ridge will not be smoothed (see Figure 3). We show in experiments (Sec. 5.2) that training with $L_{\text{surface}}$ helps boost our performance. It’s worth noting that our approach is faster than plane fitting [40], and is more accurate than simple partial derivatives (please find more detailed comparison in Appendix A). This is crucial since we need to re-compute surface normal for each training sample as required by the data augmentation in Sec. 3.3.

**Depth prediction loss.** We penalize the average $\ell_2$ depth difference compared to the ground truth: $L_{\text{avg}} = \left( \sum_p d_p - \sum_p \hat{d}_p \right)^2 / q$. We use reverse Huber loss berHu$(d, \hat{d})$ to penalize the per-pixel prediction error, which has shown...
superiority in single image depth estimation [25]. We set the cut-off rate \( c = 0.2 \max_p (|d_p - \hat{d}_p|) \) for each batch.

### 3.3. Implementation details

In inference, for each input image \( I \) and the object mask \( M_{\text{object}} \), we first perform the largest center crop with the same aspect ratio as the network input size, then resize \( I \) to fit the network input size. The output depth map is then resized back to the same scale as the original cropped image by bilinear interpolation.

**Mask dropout.** Initial experiments indicated that depth regressions against images tend to have quite localized support, likely because very high spatial correlations in real images mean that large-scale support is superfluous. But a network that predicts depth in locations where there are no known pixel values needs to have spatial support on very long scales (so that a location where pixel values aren’t known can draw from locations where the pixels are known). To achieve this, we randomly flip each pixel value in the object mask with a chance of 10%, meaning a mask dropout rate of 0.1. This forces the network to be able to use nearby pixels to predict depths. We mask out the flipped pixels when computing the loss to avoid error backpropagation. We show in experiments (Sec. 5.2) that training with mask dropout helps stabilize our performance.

**Data Augmentation.** During training, we perform random cropping instead of center cropping to increase the training samples. The window size varies between the fraction \( \alpha = \frac{3}{4}, \frac{1}{2} \) of the size of the largest center crop. We perform the same cropping for the ground truth depth map \( d \). Note that a smaller cropping is equivalent to a closer view of the object, resulting in a smaller distance to the camera. We thus divide each pixel value \( d \) with \( \alpha \) in order to preserve the depth scales across different crops of the same image. We also update each crop’s normal given the re-scaled depth, using the weighted quantized smoothed normal computation as described in Sec. 3.2. Moreover, we perform random rotation on the image plane ranges in \([-5, 5]\) degrees, random horizontal flipping and image color changes with each of the RGB channel being multiplied by the weight ranges in \([0.8, 1.2]\) independently. Each augmentation parameter is uniformly and randomly sampled from the defined range.

### 4. Dataset

#### 4.1. Training

To train our method, we need triples of ground truth: RGB image, object mask, depth with masked object being removed. Such datasets do not exist, and are difficult to make on a large scale. Instead, we make the ground truth tuples by rendering a synthetic dataset. However, a rendered dataset may not properly represent texture or illumination. We thus combine the data with the standard NYUv2 [40] real dataset (where we have only empty object masks). Training samples are selected uniformly across each training set (synthetic or real), with a 50% probability of choosing one or another. We apply mask dropout on all object masks.

**Synthetic:** AI2-THOR [23] is an indoor virtual environment that supports physical simulation of objects in the scene. We modified the default simulation setting to be able to remove every object in the scene, rather than pickupable objects only. AI2-THOR has 120 predefined scenes from four categories of rooms: kitchen, living room, bedroom and bathroom. In each scene, we place an agent at a random location for 100 times. The height of agent is sampled under the normal distribution with mean of 1.0m and a standard derivation (std) of 0.1m. The agent looks at the scene with a randomly sampled altitude, which is normally distributed with a mean of \( 0^\circ \) (looking at horizon) and a std of \( 10^\circ \). At each view, we generate the ground truth depth map with one of the objects removed. For each type of room, we use 27 scenes for training and withhold three scenes for testing. This creates 47k \( 640 \times 480 \) image-depth pairs of synthetic samples. Each rendered depth map ranges up to 5 meters.

**Real:** NYUv2 [40] is one of the widely used RGBD dataset with real indoor scenes. We use the official train and test split in our experiment.

#### 4.2. Testing

**Synthetic.** We use the test split of AI2-THOR to compare with other baselines. We obtain 1162 test samples with depth changes of at least 0.25m per pixel after the object is removed. Slight changes in depth can hardly be examined the performance.
1.5m, 2.0m wall, empty space, other objects variables with our approach to estimate image depth. In this case we’re “Do nothing” approach, we compare with three classes of natural baselines:

- Predict depth from the inpainted one using our approach.
- DepthComp requires additional input of semantic segmentation maps. We use the outputs from SegNet [3] trained on SUNRGBD [41] to run the experiment.
- (3) Image inpainting. Given the object mask, we inpaint the RGB image using the method by lizuka et al. [18], then predict depth from the inpainted one using our approach.

For fair comparison, we use our network with no object mask to produce the initial depth map for all baselines. We evaluate the performance of our approach and all the baselines using the following standard single image depth estimation evaluation metrics:

- \( \text{rms} \): root mean squared error: \( \sqrt{\frac{1}{Q} \sum_{p} (d_p - \hat{d}_p)^2} \)
- \( \text{mae} \): mean absolute error: \( \frac{1}{Q} \sum_{p} |d_p - \hat{d}_p| \)
- \( \text{rel} \): mean absolute relative error: \( \frac{1}{Q} \sum_{p} \frac{|d_p - \hat{d}_p|}{d_p} \)
- \( \delta_i \): percentage of pixels where the ratio (or its reciprocal) between the prediction and the label is within a threshold, 1.25, to the power \( i \):
  \[
  \frac{1}{Q} \sum_{p} 1[\max(\frac{\hat{d}_p}{d_p}, \frac{d_p}{\hat{d}_p}) < 1.25^i]
  \]
  We set \( i = \{1, 2, 3\} \).

Note that rms, mae, and rel are error metrics (the lower the better) and \( \delta_i \) measures accuracy (the higher the better). For detailed analysis, we calculate the average pixel performance using the metrics on the entire image (all pixels), the region inside the mask (interior), and the region outside the mask (exterior). Performance on the entire image naturally shows the ability of predicting image depth with an object removed; performance on the interior region demonstrates the ability to predict the scene depth behind the object; and performance on the exterior region demonstrates the ability of predicting the depth of non-removed area.

5. Experiments

Experimental setup. We implement our network using MatConvNet and train it on a single NVIDIA Titan X GPU. We use the weights of pretrained ResNet-50 on ImageNet to initialize the the encoder, then train the whole network end-to-end. We use ADAM [22] to update network parameters with a batch size of 32 and an initial learning rate of 0.01. The learning rate is then halved after every 5 epochs and the whole training procedure takes around 20 epochs to converge. In our experiment, we set the term weights in Eq. 1 as: \( w_1 = 1, w_2 = 0.5, w_3 = 1 \).

Baselines. To demonstrate the effectiveness of our approach, we compare with three classes of natural baselines: (1) “Do nothing”. We simply ignore the mask and apply our approach to estimate image depth. In this case we’re predicting image depth with the object. (2) Depth inpainting. We use the object mask to remove the object from our predicted depth map, then fill in the hole using three different methods. For the first method, we apply Poisson editing [36] to interpolate the missing depth based on neighboring depth values. For the second method, we apply a vanilla auto-encoder. The auto-encoder gets as input the concatenation of the depth map and the object mask, and predicts the scene depth with the object removed. The encoder (decoder) consists five convolution layers with kernel size of \( 3 \times 3 \), with max pooling (scale factor 2) and ReLU in between, resulting in the same \( 8 \times 10 \) bottleneck feature size as ours. We train the auto-encoder with the same setting as our approach. For the third method, we compare to the state-of-the-art depth hole filling approach DepthComp by Atapour et al. [1]. DepthComp requires additional input of semantic segmentation maps. We use the outputs from SegNet [3] trained on SUNRGBD [41] to run the experiment.

We show in Figure 5 our qualitative performance compared with other baselines on NYUd v2 dataset. NYUd v2 does not have ground truth depth with the object removed, so we could only compare qualitatively. We use the ground truth 2D segmentation in NYUd v2 as the input object mask. Our approach is able to produce well-behaved depth behind the object and the depth of non-removed area, along with a good normal estimates for the hidden geometry. Note that depth predictions

| Factor | variables |
|--------|-----------|
| shape complexity | simple (e.g. box), complex (e.g. chair) |
| shape rarity | common (e.g. box), rare (e.g. doll) |
| number of objects close by | wall, empty space, other objects |
| object behind | 1.5m, 2.0m |

Table 1. Factors and variables used to construct our dataset.
Figure 5. Qualitative results of depth estimation with the object *removed* on the NYUv2 dataset [40]. We compare our approach to several baselines. We show in the second row the ground truth scene depth with all the object *non-removed*. For image inpainting baseline we also show the inpainted RGB image for analysis. The surface normal is derived from the predicted depth. Our method is able to estimate the hidden geometry behind the cupboard when the printer is removed (column 1); the space on top of the bed when the pillow is removed (column 2); and the space below the ream of paper when the shelves but not that paper are removed (column 3). Best viewed in color.

by the inpainting baseline are mangled by inpainting errors. Poisson smoothing produces somewhat better estimates, but fails in the obvious way when one side of the background is closer than the other (first column). We show in Figure 6 more qualitative results on our collected real dataset and the synthetic AI2-THOR dataset.
Table 2. Depth estimation performance with object removed compared with other baselines on the synthetic AI2-THOR test set. We evaluate average pixel performance on all image pixels (All Pixels), pixels inside the object mask (Interior) and pixels outside the object mask (Exterior). All baselines get initial depths (without object remove) from our method with the object masked out. The "*" in exterior columns means that the method does not produce pixels in this region. The best shows the best score in each column.

| Method                  | All Pixels   | Interior       | Exterior       |
|-------------------------|--------------|----------------|----------------|
|                          | All Pixels   | Interior       | Exterior       |
| Do nothing              | .647 .368    | 207 67.0 .90   | 96.6 99.6 .99 | .600 .513 .267 .358 67.6 97.0 | .430 .355 .201 69.9 92.7 99.8 |
| Poisson                 | .437 .352    | .198 69.6 .92  | 98.8 | .394 .320 .168 66.8 93.9 99.9 | * * * * * * * |
| DepthComp               | .438 .360    | .203 68.0 .91  | 99.7 | .513 .242 .225 47.9 79.7 98.8 | * * * * * * * |
| Inpaint                 | .338 .434    | .258 60.2 .86  | 98.9 | .526 .445 .235 52.3 92.6 99.8 | .539 .433 .260 60.9 85.9 98.8 |
| Auto-encoder            | .341 .360    | .192 66.0 .95  | 100 | .353 .290 .153 70.5 97.7 100.0 | .437 .366 .196 65.5 94.7 100.0 |
| Ours                    | .425 .349    | .198 70.6 .93  | 99.8 | .310 .247 .133 81.9 99.6 100.0 | .435 .359 .204 69.5 92.4 99.8 |
| Ours w/o mask dropout   | .762 .612    | .272 38.9 .71  | 90.1 | .517 .416 .203 51.3 87.5 99.3 | .781 .630 .279 57.7 69.7 89.3 |
| Ours w/o norm           | .455 .364    | .188 66.7 .93  | 99.3 | .393 .316 .160 68.8 96.0 99.8 | .460 .369 .191 66.5 93.4 99.2 |

Table 3. Depth estimation performance with object removed compared with other baselines on our collected real dataset. We evaluate average pixel performance on all image pixels (All Pixels), pixels inside the object mask (Interior) and pixels outside the object mask (Exterior). All baselines get initial depths (without object remove) from our method with the object masked out.

| Method                  | All Pixels   | Interior       | Exterior       |
|-------------------------|--------------|----------------|----------------|
|                          | All Pixels   | Interior       | Exterior       |
| Do Nothing              | .647 .368    | 207 67.0 .90   | 96.6 99.6 .99 | .600 .513 .267 .358 67.6 97.0 | .430 .355 .201 69.9 92.7 99.8 |
| Poisson                 | .437 .352    | .198 69.6 .92  | 98.8 | .394 .320 .168 66.8 93.9 99.9 | * * * * * * * |
| DepthComp               | .438 .360    | .203 68.0 .91  | 99.7 | .513 .242 .225 47.9 79.7 98.8 | * * * * * * * |
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| Ours w/o mask dropout   | .762 .612    | .272 38.9 .71  | 90.1 | .517 .416 .203 51.3 87.5 99.3 | .781 .630 .279 57.7 69.7 89.3 |
| Ours w/o norm           | .455 .364    | .188 66.7 .93  | 99.3 | .393 .316 .160 68.8 96.0 99.8 | .460 .369 .191 66.5 93.4 99.2 |
Figure 7. Qualitative results of depth estimation with multiple objects removed on the NYUv2 dataset [40]. In the first row, we show from left to right the input RGB image, ground truth depth with all objects and the derived surface normal. In each following example we show from left to right the input object mask, our predicted depth with the object(s) removed and the derived surface normal. We show seven different input object masks as different combinations of three objects: a bookshelf, a ream of paper on the bookshelf, and the box beside the bookshelf. Our network is able to remove object(s) within the supplied mask and retain other objects in the scene.

Depth with multiple objects removed. One important benefit of using object mask as input is that we can arbitrarily remove any number of objects from the scene and predict the depth without these objects. Figure 7 demonstrates the ability of our network to estimate scene depth with different combinations of objects removed from the same scene. Our approach is also able to produce consistent predictions for non-removed area (e.g. layouts, counter) in the same scene.

5.2. Quantitative results

We show in Table 2 our quantitative comparison on the test set of the synthetic AI2-THOR dataset. Table 3 reports the performance on our collected real dataset. Poisson and DepthComp do not perturb depth outside the object mask region, hence, their exterior region is equal to “Do nothing”. We report their error metrics in exterior as *. Our method outperforms all baselines on most metrics. Inpainting method does not work; Poisson and DepthComp have trouble removing an object. Auto-encoder and ours produce comparatively good interior (ours still slightly better) depth, but Auto-encoder produces worse depth estimates of exterior region. Note that for some measurements the depth prediction performance inside the object masked could be better than the prediction on the whole image scale. We believe that it’s uncommon that objects mask other clutter, so the masked scene tends to be walls, floors, etc., where depth has simpler statistics and is easier to predict.

Ablation study. We show in Table 2 and Table 3 the performance gains by training with our smoothed ground truth normal loss (ours v.s. ours w/o normal) and the mask dropout data augmentation (ours v.s. ours w/o mask).

Factors that affect error. We investigate how properties of test data affect the error of the method, by regressing error against the attributes of the test images (Sec. 4.2) and looking for significant predictors. We use both individual terms and pairwise interactions, and apply an ANOVA. Please find detailed analysis in Appendix E.

Single image depth with the object. For images where no object is removed, our approach is able to predict scene depth that is of comparable quality to that of state-of-the-art single image depth estimation methods. Please find detailed evaluations in Appendix B.

6. Conclusion

We have introduced a new task – estimating the hidden geometry behind the object. Our method takes as input a single RGB image and an object mask, and predicts a depth map that describes the scene when the object is removed. We show, both qualitatively and quantitatively, that our approach is able to predict depth behind objects better than other baselines, and is flexible in removing multiple objects. Our approach can be further utilized for applications like object insertion and manipulation in a single RGB image.

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A. Evaluation of Surface Normal Computation

Due to the small magnitude of noise of the measurement error presented by the data collected from sensors in the real world (e.g. NYUd v2), it is difficult to directly calculate reliable surface normals from the depth map to train from. The error in surface normal ground truth will greatly affect the quality of the depth estimation. To incorporate $L_{surface}$ in the training procedure, we thus propose our smoothed surface normal ground truth computation in Sec. 3.2 in the main paper.

We demonstrate the efficacy of our surface normal computation compared to other methods on the synthetic AI2-THOR test set. AI2-THOR has accurate ground truth depth and surface normal without sensor error. We obtain the ground truth surface normal by computing the first-order derivatives from the ground truth depth. Then we simulate a measurement error by adding some random noises. We model those noises as a combination of a white noise (0.001 m) and a circle patch of diameter of 5 pixels (0.01 m) added randomly to the scene with a probability of 0.01. We shown in Table 4 the comparison between our surface normal computation, the simple gradient-based approach and the plane fitting approach [40]. “Accuracy” is defined as the average dot product between the computed surface normal and the ground truth (higher the better, ranges from -1 to 1). “Speed” reports the time (second) used per image. Note that our method and the gradient-based approach run on single gpu (NVIDIA Titan X) while plane-fitting runs on single cpu (1.7 GHz, 8 cores). We observed that the accuracy is highly dependent on a noise type: if we only add the random circle patch with a probability of 0.02, the resulted accuracy is 0.917, 0.831, and 0.881 respectively.

In all, those experiments demonstrate that our surface normal computation produces high enough quality and is fast enough to be incorporated in network training.

B. Single Image Depth Estimation with the Object

While this is not our objective, we also evaluate our performance with no object removed – same as single image depth estimation. We directly test our trained network that predicts depth with the object removed on NYUd v2 dataset and set the input object mask as empty. Table 5 compares our method to a variety of the state-of-the-art on the NYUd v2 dataset and our collected real evaluation dataset. Though our approach is trained for a different task, we show on-par performance. We consider the main comparison with Laina et al., since we have the similar encoder-decoder

| Method            | rms    | rel   | $\delta_1$ | $\delta_2$ | $\delta_3$ |
|-------------------|--------|-------|------------|------------|------------|
| NYUd v2 [40]      |        |       |            |            |            |
| Saxana et al. [38]| 1.214  | 0.349 | 44.7       | 74.5       | 89.7       |
| Eigen et al. [12] | 0.877  | 0.214 | 61.4       | 88.8       | 97.2       |
| Eigen & Fergus [11]| 0.641  | 0.158 | 76.9       | 95.0       | 98.8       |
| Laina et al. [25] | 0.573  | 0.127 | 81.1       | 95.3       | 98.8       |
| Ma & Karaman [32] | 0.514  | 0.143 | 81.0       | 95.9       | 98.9       |
| Kendall [20]      | 0.506  | 0.110 | 81.7       | 95.9       | 98.9       |
| Ours              | 0.642  | 0.142 | 80.1       | 94.6       | 98.4       |

Table 5. Single image depth estimation compared with the state-of-the-art on the NYUd v2 dataset (top) and our collected real dataset (bottom). We directly test our trained approach that predicts depth with the object removed. In this case, our method gets an empty object mask (no object to be removed). Our approach shows on-par performance. Our approach does not obtain performance gain with more training data (AI2-THOR) but rather gets performance drop on NYUd v2. This is because the depth distributions of the two dataset are different and training with both datasets will slightly harm performance on each other, as illustrated in Figure 8.

Figure 8. Illustration of the different depth statistic between AI2-THOR and NYUd v2 dataset. The red dashed curve shows a cumulative distribution (cdf) of depths in the AI2-THOR dataset, which is notably biased toward somewhat smaller depths (there are no depths greater than 5 meters). The blue solid curve shows a cdf for the depths in NYUv2, which has a greater proportion of large depths. The frequency can be read on the left axis. Dark bars show the mean error in a given depth range for our method run on NYUv2; light bars show the same for the method of Laina et al. Note that, in the closer depth domains that are more frequent in AI2-THOR, the two methods have comparable error; our method makes depth errors mostly on the relatively unfamiliar large depths (and Laina’s method makes depth errors on the less familiar small depths in AI2-THOR). Best view in color.
structure. Our method outperforms Laina et al. on our collected dataset but shows performance degrades on NYUd v2. We realized that this is due to the different depth statistic between the synthetic and real dataset. In Figure 8, we show that depth maps in AI2-THOR range up to 5 meters, compared to the maximum depth of 10 meters in NYUd v2. This biases the depth predictor to be in favor of the shallower depth. As a result, our network trained on both NYUd v2 and AI2-THOR makes more significant (RMS) error on the depth prediction that is deeper than 5 meters on NYUd v2 test set in comparison to Laina et al. [25]. However, it is unavoidable for us to not to use the synthesis dataset, since it is the only source that we can easily manipulate the scene to have ground truth depth with the object removed.

In all, we conclude that our method, like others, performs very strongly on test sets where the distribution of depths compares to that in training, but degrades when it encounters novel depths.

C. Our Collected Evaluation Dataset

We show in Table 6 the detailed configurations of our collected evaluation dataset. The configurations are based on the five factors we investigate that might affect prediction error. The top $2 \times 2$ sub-table considers the object’s characteristics itself: common or rare, simple or complex. The bottom sub-table, which has three rows, considers the variables of the spatial relationship with the scene: numbers of objects close by, the non-removed objects behind and the distance to the camera. We show typical samples of each of the five factors in the table.

D. More Qualitative Results

We show in Figure 9 and Figure 10 more qualitative results on the NYUd v2 dataset. Our method can remove objects very well. Note that our network is trained on NYUd v2 but is never trained to remove an object from this dataset (we learn to remove an object by training on AI2-THOR). Since there is no ground truth of scene depth with an object removed in NYUd v2, we are only able to show the qualitative results compared to other baselines.

Figure 11 and Figure 12 shows more qualitative results of our comparison with other baselines on the synthetic AI2-THOR dataset and our collected real dataset.

| Simple | Complex |
|--------|---------|
| Common | ![Sample Image] |
| Rare   | ![Sample Image] |

Table 6. Configurations of our collected evaluation dataset. We show sample images of each of the five factors we use to construct our dataset: object complexity, object rarity, numbers of objects close by, objects behind and distance to the camera. Note that the first two factors focus on the object itself and the latter three focus on the spatial relationship between the object and the scene.
Figure 9. Qualitative results of depth estimation with object removed on the NYUv2 dataset [40]. We compare our approach to several baselines. We show in the second row the ground truth scene depth with the object. For image inpainting baseline we also show the inpainted RGB image (last row) for analysis. The surface normal is derived from the predicted depth. Our method is able to estimate the depth behind the chair while preserving the depth of the person sitting on it (1st example); the depth of the flat floor after removing the chair (2nd example) and the depth of the floor behind the toilet (3rd example). Best viewed in color.
Figure 10. More qualitative results of depth estimation with the object removed on NYUv2 dataset [40]. For each sample, we show in the first row the RGB image and the object mask, the second row the ground truth depth with the object and the third row our predicted scene depth without the object. Best viewed in color.
Figure 11. Qualitative results of depth estimation with the object *removed* on synthetic AI2-THOR test set. We compare our approach to several baselines. We use our predicted scene depth with empty mask as the initial depth prediction for other baselines. Column 1 adds additional comparison to the sample in Figure 6 column 3 in the main paper. Note that our method could infer the space inside the cupboard (2nd example) and the wall behind the toilet (3rd example). Auto-encoder cannot fully remove the objects within the masked region: in the 2nd example, the predicted depth behind the cabinet door points to the wrong direction (as if it is added by a constant depth value); In the 3rd example, it makes a concave shape on the wall. Best viewed in color.
Figure 12. Qualitative results of depth estimation with the object removed on our collected evaluation set. We compare our approach to several baselines. We use ours with empty mask as the initial depth prediction for other baselines. The first two columns adds more results to the sample in Figure 6 in the main paper. Our method is able to reconstruct the depth of the floor and wall behind the bag. Best viewed in color.
E. Analysis of Variance (ANOVA)

We investigate how properties of test data affect the error of the method, by regressing error against the attributes of the test images from our collected dataset and looking for significant predictors. We use both individual terms and pairwise interactions, and apply an ANOVA. We consider the following five individual terms:

1. object complexity
2. object rarity
3. numbers of objects close by
4. background (objects) behind
5. object’s distance to the camera

The interaction terms are the 2-combination of the five individual terms, resulting in \( \binom{5}{2} = 10 \) terms.

We analyze on our approach and the two baselines: image inpainting and poisson inpainting.

E.1. Our method

For our method, only 3 of 10 interaction terms achieve significance using the usual F-test (i.e. \( p < 0.05 \)). The adjusted \( R^2 \) is 0.882, meaning the regression is quite good at predicting errors, and so it is reasonable to infer hard cases from regression coefficients. The significant cases are:

1. objects far from the camera with two other objects close by (mild increase in error rate);
2. simple objects that are far from the camera (mild decrease in error rate);
3. rare objects that are far from the camera (mild decrease in error rate).

Of the individual terms, rarity, objects behind and distance to the camera have effects, with simple objects, common objects, cluttered or empty backgrounds, and objects far from the camera are each associated with an increase in error rate. It is odd that common objects should be associated with increased error, and it is odd that objects far from the camera should be associated with increased error. The effect of objects behind is easily understood: the cases are against wall, on cluttered or on empty background, and it is relatively natural that predicting the depth to a wall an object is in contact with might be more accurate.

E.2. Image inpainting baseline

For the image inpainting baseline, again only 3 of 10 interaction terms achieve significance using the usual F-test (i.e. \( p < 0.05 \)). The adjusted \( R^2 \) is 0.633, meaning the regression is only moderate at predicting errors. This is likely because the conditions we investigate have only mild effect on whether inpainting is likely to be successful (more important is image appearance around the object). Significant effects are:

1. objects far from the camera with two other objects close by (mild decrease in error rate);
2. simple objects that are far from the camera (mild decrease in error rate);
3. rare objects that are far from the camera (mild decrease in error rate).

Note that the above effects are the same as for the inpainting baseline. Of the individual terms, complexity, rarity, objects behind and size have effects, with simple objects, common objects, cluttered or empty backgrounds, and objects far from the camera are each associated with an increase in error rate (again, the same as the inpainting baseline).

E.3. Poisson editing baseline

For the Poisson baseline, again only 3 of 10 interaction terms achieve significance using the usual F-test (i.e. \( p < 0.05 \)). The adjusted \( R^2 \) is 0.632, meaning the regression is only moderate at predicting errors. This is likely because the conditions we investigate have only mild effect on whether smoothing is likely to be successful (more important is the pool of depths around the object). Significant effects are:

1. objects far from the camera with two other objects close by (mild decrease in error rate);
2. simple objects that are far from the camera (mild decrease in error rate);
3. rare objects that are far from the camera (mild decrease in error rate).

Note that the above effects are the same as for the inpainting baseline. Of the individual terms, complexity, rarity, objects behind and size have effects, with simple objects, common objects, cluttered or empty backgrounds, and objects far from the camera are each associated with an increase in error rate (again, the same as the inpainting baseline).