Depth from a Single Image by Harmonizing Overcomplete Local Network Predictions

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Abstract

A single color image can contain many cues informative towards different aspects of local geometric structure. We approach the problem of monocular depth estimation by using a neural network to produce a mid-level representation that summarizes these cues. This network is trained to characterize local scene geometry by predicting, at every image location, depth derivatives of different orders, orientations and scales. However, instead of a single estimate for each derivative, the network outputs probability distributions that allow it to express confidence about some coefficients, and ambiguity about others. Scene depth is then estimated by harmonizing this overcomplete set of network predictions, using a globalization procedure that finds a single consistent depth map that best matches all the local derivative distributions. We demonstrate the efficacy of this approach through evaluation on the NYU v2 depth data set.

1 Introduction

In this paper, we consider the task of monocular depth estimation—i.e., recovering scene depth from a single color image. Knowledge of a scene’s three-dimensional (3D) geometry can be useful in reasoning about its composition, and therefore measurements from depth sensors are often used to augment image data for inference in many vision, robotics, and graphics tasks. However, the human visual system can clearly form at least an approximate estimate of depth in the absence of stereo and parallax cues—e.g., from two-dimensional photographs—and it is desirable to replicate this ability computationally. Depth information inferred from monocular images can serve as a useful proxy when explicit depth measurements are unavailable, and be used to refine these measurements where they are noisy or ambiguous.

The 3D co-ordinates of a surface imaged by a perspective camera are physically ambiguous along a ray passing through the camera center. However, a natural image often contains multiple cues that can indicate aspects of the scene’s underlying geometry. For example, the projected scale of a familiar object of known size indicates how far it is; foreshortening of regular textures provide information about surface orientation; gradients due to shading indicate both orientation and curvature; strong edges and corners can correspond to convex or concave depth boundaries; and occluding contours or the relative position of key landmarks can be used to deduce the coarse geometry of an object or the whole scene. While a given image may be rich in such geometric cues, it is important to note that these cues are present in different image regions, and each indicates a different aspect of 3D structure.

We propose a neural network-based approach to monocular depth estimation that explicitly leverages this intuition. Prior neural methods have largely sought to directly regress to depth [5, 6]—with some additionally making predictions about smoothness across adjacent regions [10], or predicting relative depth ordering between pairs of image points [17]. In contrast, we train a neural network with a rich

∗Part of this work was done while JS was a visiting student at TTI-Chicago.
To recover depth from a single image, we first use a neural network trained to characterize local depth structure. This network produces distributions for values of various depth derivatives—of different orders, at multiple scales and orientations—at every pixel, taking a centered local image patch as input (top left). These distributions express the ability of the network to determine different derivatives at different locations with different degrees of certainty (right). We combine these local distributions within a globalization framework, to produce a single consistent depth map estimate.

Given a local image patch, our network characterizes various aspects of the local geometric structure by predicting values of a number of derivatives of the depth map—at various scales, orientations, and of different orders (including the 0th derivative, i.e., the depth itself). However, as mentioned above, we expect different image regions to contain cues informative towards different aspects of surface depth. Therefore, instead of over-committing to a single value, our network outputs parameterized distributions for each derivative, allowing it to effectively characterize the ambiguity in its predictions. For inference, we apply our network to all overlapping patches in the input image. This gives us distributions effectively characterizing coefficients in an overcomplete representation of depth map. To recover the depth map itself, we employ an efficient globalization procedure that finds a single consistent depth map that best agrees with our local network predictions.

We evaluate our approach on the NYUv2 depth data set [13], and find that it performs competitively. Beyond the benefits to the monocular depth estimation task itself, the success of our approach suggests that our network can serve as a useful way to incorporate monocular cues in more general depth estimation settings—e.g., when sparse or noisy depth measurements are available. Since the output of our network is distributional, it can be easily combined with partial depth cues from other sources within a common globalization framework. Moreover, we expect our general approach—of learning to predict distributions in an overcomplete representation followed by globalization—to be useful broadly in tasks that involve recovering other kinds of scene value maps that have rich structure, such as optical or scene flow, surface reflectances, illumination environments, etc.

## 2 Related Work

Interest in monocular depth estimation dates back to the early days of computer vision, with methods that reasoned about geometry from cues such as diffuse shading [7], or contours [4, 14]. However, the last decade has seen accelerated progress on this task [1, 5, 6, 8–10, 12, 15–17], largely owing to the availability of cheap consumer depth sensors, that made relatively large amounts of depth data available for training learning-based methods.

Most recent methods are based on training neural networks that can map RGB images to geometry [1, 5, 6, 10, 15–17]. Eigen et al. [5, 6] set up their network to regress directly to per-pixel depth values,
although they provide deeper supervision to their network by requiring an intermediate layer to explicitly output a coarse depth map. Other methods [10, 15] use conditional random fields (CRFs) to smooth their neural estimates. Moreover, the network in [10] also learns to predict one aspect of depth structure, in the form of the CRF’s pairwise potentials.

Some methods are trained to exploit other individual aspects of geometric structure. Wang et al. [16] train a neural network to output surface normals instead of depth (Eigen et al. [5] do so as well, for a network separately trained for this task). In a novel approach, Zoran et al. [17] were able to train a network to predict the relative depth ordering between pairs of points in the image—whether one surface is behind, in front of, or at the same depth as the other. However, their globalization scheme to combine these outputs was able to achieve limited accuracy at estimating actual depth, due to the limited information carried by ordinal pair-wise predictions.

In contrast, our network learns to reason about a more diverse set of structural relationships, by predicting a large number of coefficients at each location. Note that some prior methods [1, 15] also regress to coefficients in some basis instead of to depth values directly. However, their motivation for this is to reduce the complexity of the output space, and use basis sets that have much lower dimensionality than the depth map itself. Our approach is different—our predictions are distributions over coefficients in an overcomplete representation, motivated by the expectation that our network will be able to precisely characterize only a small subset of the total coefficients in our representation.

Our overall approach is similar to, and indeed inspired by, the recent work of Chakrabarti et al. [2], who proposed estimating a scene map (they considered disparity estimation from stereo images) by first using local predictors to produce distributional outputs from many overlapping regions at multiple scales, followed by a globalization step to harmonize these outputs. However, in addition to the fact that we use a neural network to carry out local inference, our approach is different in that inference is not based on imposing a restrictive model (such as planarity) on our local outputs. Instead, we produce independent local distributions for various derivatives of the depth map. Consequently, our globalization method need not explicitly reason about which local predictions are “outliers” with respect to such a model. Moreover, since our coefficients can be related to the global depth map through convolutions, we are able to use Fourier-domain computations for efficient inference.

3 Proposed Approach

We formulate our problem as that of estimating a scene map \(y(n) \in \mathbb{R}\), which encodes point-wise scene depth, from a single RGB image \(x(n) \in \mathbb{R}^3\), where \(n \in \mathbb{Z}^2\) indexes location on the image plane. We represent this scene map \(y(n)\) in terms of a set of coefficients \(\{w_i(n)\}_{i=1}^K\) at each location \(n\), corresponding to various spatial derivatives. Specifically, these coefficients are related to the scene map \(y(n)\) through convolution with a bank of derivative filters \(\{k_i\}_{i=1}^K\), i.e.,

\[
w_i(n) = (y * k_i)(n).
\]

For our task, we define \(\{k_i\}\) to be a set of 2D derivative-of-Gaussian filters with standard deviations \(2^s\) pixels, for scales \(s = \{1, 2, 3\}\). We use the zeroth order derivative (i.e., the Gaussian itself), first order derivatives along eight orientations, as well as second order derivatives—along each of the
orientations, and orthogonal orientations. We also use the impulse filter which can be interpreted as the zeroth derivative at scale 0, with the corresponding coefficients \( w_i(n) = y(n) \). This gives us a total of \( K = 64 \) filters, that are shown in Fig. 2. We normalize the first and second order filters to be unit norm. The zeroth order filters coefficients typically have higher magnitudes, and in practice, we find it useful to normalize them as \( \|k_i\|_2 = 1/4 \) to obtain a more balanced representation.

To estimate the scene map \( y(n) \), we first use a convolutional neural network to output distributions for the coefficients \( p(w_i(n)) \), for every filter \( i \) and location \( n \). We choose a parametric form for these distributions \( p(\cdot) \), with the network predicting the corresponding parameters for each coefficient. The network is trained to produce these distributions for each set of coefficients \( \{w_i(n)\} \) by using as input a local region centered around \( n \) in the RGB image \( x \). We then form a single consistent estimate of \( y(n) \) by solving a global optimization problem that maximizes the likelihood of the different coefficients of \( y(n) \) under the distributions provided by our network. We now describe the different components of our approach (which is summarized in Fig. 1)—the parametric form for our local coefficient distributions, the architecture of our neural network, and our globalization method.

### 3.1 Parameterizing Local Distributions

We use a mixture of uni-variate Gaussians to parameterize the distribution for each coefficient \( w_i(n) \) produced by our neural network as

\[
p_{i,n}(w_i(n)) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(\frac{|w_i(n) - c_i|^2}{2\sigma_i^2}\right),
\]

where \( M \) is the number of mixture components, \( \sigma_i^2 \) is a common variance for all components for derivative \( i \), \( \{c_i\} \) are the individual component means, and \( \{\hat{p}_i(n)\} \), \( \sum_j \hat{p}_i(n) = 1 \), are the mixture weights produced by our neural network for the coefficient \( w_i(n) \), from the input image \( x(n) \).

We use \( M = 64 \) components, and determine the mixture means \( \{c_i\} \) and variances \( \{\sigma_i^2\} \) from a training set of ground truth depth maps. We use one-dimensional K-means clustering on sets of training coefficient values \( \{w_i\} \) for each derivative \( i \), and set the means \( c_i \) in (2) above to the cluster centers. We set \( \sigma_i^2 \) to the average in-cluster variance —however, since many of the derivatives have heavy-tailed distributions, we compute this average only over clusters that have more than a minimum number of assignments.

### 3.2 Neural Network-based Local Predictions

Next, we train a neural network to predict the mixture weights \( \hat{p}_i(n) \) in our parameterization in (2). Note that this is a fairly high-dimensional output space—corresponding to \( K \times M \) numbers, with \((M - 1) \times K\) degrees of freedom, at each location \( n \). We use a ten-layer convolutional feed-forward architecture detailed in Table 1, with all hidden layers followed by a ReLU. Our network shares a common set of hidden layers to output distributions for all coefficients, using an effective receptive field of \( 97 \times 97 \) centered around \( n \) in the input image to generate the distributions for all \( \{w_i(n)\} \).

This architecture is applied in a fully-convolutional way [11] during both training and inference.

In addition to local appearance of an image patch, we expect its location within the image plane to also be useful for reasoning about geometry—e.g., to map observed perspective deformations to surface orientation, or to use information about typical scene layouts. Therefore, as shown in Table 1, we concatenate a 64-dimensional “location vector” to the output of the seventh layer (the last layer with kernel size \( > 1 \)). Rather than using a hand-crafted location encoding, we learn this feature vector to be a smooth function of pixel location \( n \). Specifically, we learn a \( (W/f) \times (H/f) \times 64 \) tensor on a coarse grid, where \( W \) and \( H \) are image width and height, and \( f \) is a sub-sampling factor (64 in our

| Layer | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|-------|---|---|---|---|---|---|---|---|---|----|
| Kernel Size | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 1 | 1 | K × M |
| Stride | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| # Outputs | 128 | 128 | 192 | 256 | 512 | 1024 | 1024 | 512 | 256 | + 64 (location) |
We define the training loss $L$ we interpret the $K$-dimensional output of our network as a set of $M$-dimensional distributions \( \{ \hat{p}^i(n) \} \), given by a soft-max operation on the final outputs, for each of the $K$ coefficients $w_i(n)$ at every location $n$. We train our network with respect to a loss between the predicted $\hat{p}^i(n)$, and the best fit of the parametric form in (2) to the ground truth derivative value $w_i(n)$. Specifically, we define $q^i(n)$ in terms of the true $w_i(n)$ as:

$$ q^i(n) \propto \exp \left( -\frac{|w_i(n) - c_i|^2}{2\sigma_i^2} \right), \quad \sum_j q^i(n) = 1. \tag{3} $$

We define the training loss $L$ in terms of the KL-divergence between these vectors $q^i(n)$ and the network predictions $\hat{p}^i(n)$, weighting the loss for each derivative by its variance $\sigma_i^2$:

$$ L = -\frac{1}{NK} \sum_{i,n} \sigma_i^2 \sum_{j=1}^M q^i(n) \left( \log \hat{p}^i(n) - \log q^i(n) \right), \tag{4} $$

where $N$ is the total number of locations $n$.

### 3.3 Global Scene Map Estimation

Applying our neural network to a given input image produces a dense set of distributions $p_{i,n}(w_i(n))$ for all derivative coefficients at all locations. We combine these to form a single coherent estimate by finding the scene map $y(n)$ whose coefficients $\{w_i(n)\}$ have high likelihoods under the corresponding distributions $\{p_{i,n}\}$. We do this by optimizing the following objective:

$$ y = \arg \max_y \sum_{i,n} \sigma_i^2 \log p_{i,n} ((k_i * y)(n)). \tag{5} $$

Note that, like in (4), the log-likelihoods for different derivatives are weighted by their variance $\sigma_i^2$.

The objective in (5) is a summation over a large ($K$ times image-size) number of non-convex terms, each of which depends on scene values $y(n)$ at multiple locations $n$ in a local neighborhood—based on the support of filter $k_i$. Despite the apparent complexity of this objective, we find that approximate inference using an alternating minimization algorithm, like in [2], works well in practice.

Specifically, we create explicit auxiliary variables $w_i(n)$ for the coefficients, and solve the following modified optimization problem:

$$ y = \arg \min_{y} \arg \min_{\{w_i(n)\}} - \left[ \sum_{i,n} \sigma_i^2 \log p_{i,n} (w_i(n)) \right] + \frac{\beta}{2} \sum_{i,n} (w_i(n) - (k_i * y)(n))^2 + \frac{1}{2} \mathcal{R}(y). \tag{6} $$

Note that the second term above forces coefficients of $y(n)$ to be equal to the corresponding auxiliary variables $w_i(n)$, as $\beta \to \infty$. We iteratively compute (6), by alternating between minimizing the objective with respect to $y(n)$ and to $\{w_i(n)\}$, keeping the other fixed, while increasing the value of $\beta$ across iterations.

Note that there is also a third regularization term $\mathcal{R}(y)$ in (6), which we define as

$$ \mathcal{R}(y) = \sum_r \sum_n \| (\nabla_r * y)(n) \|^2, \tag{7} $$

using $3 \times 3$ Laplacian filters, at four orientations, for $\{\nabla_r\}$. In practice, this term only affects the computation of $y(n)$ in the initial iterations when the value of $\beta$ is small, and in later iterations is dominated by the values of $w_i(n)$. However, we find that adding this regularization allows us to increase the value of $\beta$ faster, and therefore converge in fewer iterations.

Each step of our alternating minimization can be carried out efficiently. When $y(n)$ fixed, the objective in (6) can be minimized with respect to each coefficient $w_i(n)$ independently as:

$$ w_i(n) = \arg \min_w - \log p_{i,n}(w) + \frac{\beta}{2\sigma_i^2} (w - \hat{w}_i(n))^2, \tag{8} $$

implementation). This tensor is bi-linearly up-sampled to the full image resolution and concatenated to the seventh layer, and learned by propagating loss gradients back through the up-sampling process.

We interpret the $K \times M$ dimensional output of our network as a set of $M$-dimensional distributions \( \{ \hat{p}^i(n) \} \), given by a soft-max operation on the final outputs, for each of the $K$ coefficients $w_i(n)$ at every location $n$. We train our network with respect to a loss between the predicted $\hat{p}^i(n)$, and the best fit of the parametric form in (2) to the ground truth derivative value $w_i(n)$. Specifically, we define $q^i(n)$ in terms of the true $w_i(n)$ as:

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where $N$ is the total number of locations $n$.
where \( \bar{w}_i(n) = (k_i \ast y)(n) \) is the corresponding derivative of the current estimate of \( y(n) \). Since \( p_{i,n}(\cdot) \) is a mixture of Gaussians, the objective in (8) can also be interpreted as the (scaled) negative log-likelihood of a Gaussian-mixture, with “posterior” mixture means \( \bar{w}_i^2(n) \) and weights \( \hat{p}_i^2(n) \):

\[
\bar{w}_i^2(n) = \frac{c_i^2 + \beta \bar{w}_i(n)}{1 + \beta}, \quad \hat{p}_i^2(n) \propto \hat{p}_i^1(n) \exp \left( -\frac{\beta}{\beta + 1} \frac{(c_i^2 - \bar{w}_i(n))^2}{2\sigma_i} \right). \tag{9}
\]

While there is no closed form solution to (8), we find that a reasonable approximation is to simply set \( w_i(n) \) to the posterior mean value \( \bar{w}_i^2(n) \) for which weight \( \hat{p}_i^2(n) \) is the highest.

The second step at each iteration involves minimizing (6) with respect to \( y \) given the current estimates of \( w_i(n) \). This is a simple least-squares minimization given by

\[
y = \arg \min_y \beta \sum_{i,n} \left( (k_i \ast y)(n) - w(n) \right)^2 + \sum_{r,n} ||(\nabla_r \ast y)(n)||^2. \tag{10}
\]

Note that since all terms above are related to \( y \) by convolutions with different filters, we can carry out this minimization very efficiently in the Fourier domain.

We initialize our iterations by setting \( w_i(n) \) simply to the component mean \( c_i^2 \) for which our predicted weight \( \hat{p}_i^2(n) \) is highest. Then, we apply the \( y \) and \( \{w_i(n)\} \) minimization steps alternatingly, while increasing \( \beta \) from \( 2^{-10} \) to \( 2^{7} \), by a factor of \( 2^{1/8} \) at each iteration.

## 4 Experimental Results

We train and evaluate our method on the NYU v2 depth dataset [13]. To construct our training and validation sets, we adopt the standard practice of using the raw videos corresponding to the training images of the official train/test split. We randomly select 10% of these videos for validation, and use the rest for training our network. Our training set is formed by sub-sampling video frames uniformly, and consists of roughly 56,000 color image-depth map pairs. Monocular depth estimation algorithms are evaluated on their accuracy in the 561 × 427 crop of the depth map that contains a valid depth projection (including filled-in areas within this crop). We use the same crop of the color image as input to our algorithm, and train our network accordingly.

We let the scene map \( y(n) \) in our formulation correspond to the reciprocal of metric depth, i.e., \( y(n) = 1/z(n) \). While other methods use different compressive transform (e.g., [5, 6] regress to \( \log z(n) \)), our choice is motivated by the fact that points on the image plane are related to their world co-ordinates by a perspective transform. This implies, for example, that in planar regions the first derivatives of \( y(n) \) will depend only on surface orientation, and that second derivatives will be zero.

### 4.1 Network Training

We use data augmentation during training, applying random rotations of \( \pm 5^\circ \) and horizontal flips simultaneously to images and depth maps, and random contrast changes to the images. We use a fully convolutional version of our architecture during training with a stride of 8 pixels, which gives us nearly 4000 training patches per image. We train our network using SGD, using a batch size of only one image. We use a momentum value of 0.9, and begin by training our network with a learning rate of 0.01 for four epochs. We train for another four epochs at a rate 0.005. We then train for two epochs each with learning rates of \( 2.5 \times 10^{-3} \) and \( 1.25 \times 10^{-3} \), and one epoch each with \( 6.25 \times 10^{-4} \) and \( 3.125 \times 10^{-4} \). During the last epoch, we periodically evaluate our network on a validation set, and retain the version that produces the best post-globalization depth estimates.

### 4.2 Evaluation

We begin by analyzing the informativeness of individual distributional outputs from our neural network. Figure 3 visualizes the accuracy and confidence of the local per-coefficient distributions produced by our network on two validation images. For coefficients of various derivative filters, we display maps of the absolute error between the true coefficient values \( w_i(n) \) and the mean of the corresponding predicted distributions \( \{p_{i,n}(\cdot)\} \). Alongside these errors, we also visualize the network’s “confidence” in terms of a map of the standard deviations of \( \{p_{i,n}(\cdot)\} \). We see that the
Figure 3: We visualize the informativeness of the local predictions from our network on two validation images. For each image, we show the accuracy and confidence of the predicted distributions for coefficients of different derivative filters (shown inset), in terms of the error between the distribution mean and true coefficient value, and the distribution standard deviation respectively. We find that errors are always low in regions of high confidence (low standard deviation). We also find that despite the fact that individual coefficients have many low-confidence regions, our globalization procedure is able to combine them to produce an accurate depth map.

Figure 4: Example depth estimation results on NYU v2 test set.

network makes high confidence predictions for different derivatives in different regions, and that the number of such high confidence predictions is least for zeroth order derivatives. Moreover, we find that all regions with high predicted confidence (i.e., low standard deviation) also have low errors.

Figure 3 also displays the corresponding global depth estimates, along with their accuracy relative to the ground truth. We find that despite having large low-confidence regions for individual coefficients,
Table 2: Effect of Individual Derivatives on Global Estimation Accuracy (on 50 validation images)

| Filters                          | Lower Better | Higher Better | \( \delta < 1.25 \) | \( \delta < 1.25^2 \) | \( \delta < 1.25^3 \) |
|----------------------------------|--------------|---------------|----------------------|----------------------|----------------------|
| Full                             | 0.7894       | 0.2900        | 0.2335               | 0.2373               | 0.6454               | 0.8817               | 0.9649               |
| Scale 0.1 (All orders)           | 1.0617       | 0.3709        | 0.3029               | 0.3487               | 0.5359               | 0.8115               | 0.9197               |
| Order 0                          | 1.3813       | 0.4509        | 0.3777               | 0.7488               | 0.4550               | 0.7281               | 0.8684               |
| Order 0.1 (All scales)           | 0.7968       | 0.2922        | 0.2355               | 0.2419               | 0.6422               | 0.8793               | 0.9631               |
| Scale 0 (Pointwise Depth)        | 1.0702       | 0.3797        | 0.3029               | 0.4010               | 0.5090               | 0.7894               | 0.9136               |

Table 3: Depth Estimation Performance on NYUv2 [13] Test Set

| Method                          | Lower Better | Higher Better | \( \delta < 1.25 \) | \( \delta < 1.25^2 \) | \( \delta < 1.25^3 \) |
|---------------------------------|--------------|---------------|----------------------|----------------------|----------------------|
| Proposed                        | 0.770        | 0.270         | 0.208                | 0.195                | 0.650                | 0.895                | 0.968                |
| Wang [15] (Depth only)          | 0.823        | 0.284         | 0.207                | 0.216                | 0.550                | 0.861                | 0.969                |
| Eigen 2014 [6]                  | 0.877        | 0.283         | 0.214                | 0.204                | 0.614                | 0.888                | 0.972                |
| Liu [10]                        | 0.824        | 0.230         |                      |                      | 0.614                | 0.883                | 0.971                |
| Zoran [17]                      | 1.22         | 0.43          | 0.41                 | 0.57                 | -                    | -                    | -                    |
| Ladicky [9]                     | -            | -             | -                    | -                    | 0.542                | 0.829                | 0.940                |
| Karsch [8]                      | 1.2          | 0.350         | -                    | -                    | -                    | -                    | -                    |
| Eigen 2015 [5] (VGG)*           | 0.641        | 0.214         | 0.158                | 0.121                | 0.769                | 0.950                | 0.988                |
| Wang [15] (Joint w/ seg)*       | 0.745        | 0.262         | 0.220                | 0.210                | 0.605                | 0.890                | 0.970                |

* Trained with additional supervision.

Our final depth map is still quite accurate. This suggests that the information provided by different coefficients' predicted distributions is complementary. To quantitatively characterize the contribution of the various components of our overcomplete representation, we conduct an ablation study on fifty validation images. Using the same trained network, we include different subsets of filter coefficients for global estimation—leaving out either specific derivative orders, or scales—and report their accuracy in Table 2 (see [6] for definitions of the performance metrics). We find that removing each of these subsets degrades the performance of the global estimation method—with the inclusion of second order derivatives contributing least to final estimation accuracy. Interestingly, we find that when using only zeroth order derivatives, combining multiple scales yields poorer results than using just the point-wise depth distributions.

Finally, we evaluate the performance of our method on the NYU v2 test set. Figure 4 shows examples of our predicted depth maps, while Table 3 reports the quantitative performance of our method, along with other state-of-the-art approaches, over the entire test set. In comparison to other methods that are trained only on the NYU v2 depth data, we find that our approach yields superior performance on most metrics. However, we note that two methods that are trained with additional supervision do perform better—Wang et al. [15] who use a network jointly trained with semantic segmentation targets (we also separately report their results for a network trained only on depth), and Eigen and Fergus [5] who use global features from a pre-trained VGG network [3].

5 Conclusion

In this paper, we described an alternative approach to reasoning about scene geometry from a single image. Instead of formulating the task as a regression to point-wise depth values, we trained a neural network to probabilistically characterize local coefficients of the scene depth map in an overcomplete representation. We showed that these local predictions could then be reconciled to form an estimate of the scene depth map using an efficient globalization procedure. We demonstrated the utility of our approach by evaluating it on the NYU v2 depth benchmark.

Its performance on the monocular depth estimation task suggests that our network’s local predictions effectively summarize the depth cues present in a single image. In future work, we will explore how these predictions can be used in other settings—e.g., to aid stereo reconstruction, or improve the quality of measurements from active and passive depth sensors. We are also interested in exploring whether our approach of training a network to make overcomplete probabilistic local predictions can be useful in other applications, such as motion estimation or intrinsic image decomposition.
Acknowledgments

AC and GS thank NVIDIA corporation for donations of Titan X GPUs that were used in this research. AC was supported by a gift from Adobe Systems.

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