Learning Ordinal Relationships for Mid-Level Vision

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Abstract

We propose a framework that infers mid-level visual properties of an image by learning about ordinal relationships. Instead of estimating metric quantities directly, the system proposes pairwise relationship estimates for points in the input image. These sparse probabilistic ordinal measurements are globalized to create a dense output map of continuous metric measurements. Estimating order relationships between pairs of points has several advantages over metric estimation: it solves a simpler problem than metric regression; humans are better at relative judgements, so data collection is easier; ordinal relationships are invariant to monotonic transformations of the data, thereby increasing the robustness of the system and providing qualitatively different information. We demonstrate that this framework works well on two important mid-level vision tasks: intrinsic image decomposition and depth from an RGB image. We train two systems with the same architecture on data from these two modalities. We provide an analysis of the resulting models, showing that they learn a number of simple rules to make ordinal decisions. We apply our algorithm to depth estimation, with good results, and intrinsic image decomposition, with state-of-the-art results.

1. Introduction

Mid-level vision involves the estimation of physical properties of pixels within an image. Examples of such problems are depth extraction, surface normal orientation estimation, intrinsic image decomposition, segmentation and shadow detection/removal [23, 4, 35, 13, 20, 22, 34]. Usually, metric (continuous valued) estimates are required at each pixel location. However, there are many cases where such a quantity may be hard to extract, or even if estimated, may be irrelevant to the task at hand. Consider looking at a piece of paper on top of a table: it would be hard to say how much closer the paper is to the observer, since the metric difference is tiny. An ordinal relation between the paper and the table, however, is clearly present. A similar case happens in outdoor scenes: looking at a range of mountains, it is usually easy to say which mountain is in front of which, but metric distances between them may be hard to estimate by sight alone. Another example is the estimation of surface albedo (reflectance) within an image. It can be difficult to give a precise albedo estimate, and this has been shown by experiments on lightness perception [9]. On the other hand, it is natural for an observer to say which of two points has darker or lighter reflectance. Only in rare cases do humans fail at this task, and such cases can be newsworthy, as in the Internet controversy over the color of a particular dress [1].

Ordinal relationships and rankings have been the subject of much research in computer vision [6, 26, 27], ma-
chine learning [7] and psychophysics [9]. There is strong
e empirical evidence that people are better at estimating ordi-
nal relations between points in scenes than estimating met-
ric quantities [33]. Such relationships have several attrac-
tive properties that make them suitable for vision applica-
tions. They have a simple, discrete three way classification
structure (corresponding to the “equality”, “less than”, and
“greater than” relationships). They are invariant to mono-
tonic transformations of the data, making them more robust
than metric estimates to variations of illumination, view-
point or pose. Since humans find them easier to estimate,
they can help us collect ground truth data for cases where
metric estimates would be hard to acquire.

In this paper we propose a framework that tackles mid-
level vision problems by learning from ordinal relation-
ships. We train a deep neural net to estimate the ordinal
relationships between point pairs in a given image. These
estimates are then aggregated to provide a full explanation
of the image (see Figure 1). We demonstrate the system
on two modalities: reflectance and depth. We show that
the same system architecture can learn from these different
modalities and provide an analysis for the kind of decision
rules the system may have learnt. We show that we achieve
competitive results in depth from single image and state-of-
the-art results on intrinsic image decomposition.

2. Related Work

A characterization of mid-level vision problems is due to
Marr [23], where localized primitives such as pixel values,
edges and corners are used to provide more global descrip-
tions of a scene. The estimation of depth, reflectance and
shading, and segmentation are important mid-level vision
tasks. We refer to the reader to [38] and [31] for good re-
views.

Most work that extracts reflectance and shading from a
single image relies on engineered priors [14, 12, 28, 21].
These models usually use cues such as gradient characteri-
izations of reflectance and shading [18] or sparsity of albedo
values in a given image [28]. Smoothness priors are also
used in most reflectance models. Depth extraction from a
single image has proven to be a harder problem, and almost
all existing models make strong assumptions such as known
illumination or shading [15, 35]. A notable exception is the
recent work of Barron and Malik [4], which uses a number
of physics-based models to recover reflectance, depth and
illumination from a single RGB or RGB-D image. How-
ever, the restriction in their case is either the requirement of
an external depth map from a depth sensor, or the presence
of only a single object in the image (with a mask outlining
the silhouette).

Learning-based approaches provide an alternate mecha-
nism to hand-designed priors. However, reliable models
for mid-level problems could not be learnt in the past due
to the absence of large-scale datasets, except for specific
synthetic datasets such as [10]. In the case of depth, the
availability of cheap depth sensors has given rise to datasets
such as NYU Depth [25]. These open up the possibility of
learning priors directly from the data, and recent works give
excellent results for depth estimation from a single RGB image [8, 20, 34, 22], showing the power of learnt models.
There have been relatively few works on learning intrinsic
image decompositions [12, 32] - perhaps due to the lack of
data. However, the recently released Intrinsic Images in the
Wild (IIW) [5] provides a large amount of data, and several
works concurrent with our own have learnt from this data
[24, 40].

Almost all existing models try to predict metric depth
or reflectance values given an input image. An alternative,
considered in this paper, is to predict ordinal relationships
between pairs of points and use those to recover a metric
estimate. Ordinal features have been successfully used in
many applications in previous work, such as image corre-
spondence [6], attribute prediction [27], face recognition
[29], and texture classification [26]. The concurrent works
of [24, 40] also learn ordinal classifiers for reflectance, but
do not apply their frameworks to depth.

3. Framework

Our framework has three main components. The first one
selects point pairs \((i, j)\) from the image. The second com-
ponent performs ordinal relationship estimation for each
pair: extracting the relevant information from the image
and providing a three-way classification. Finally, the third
component takes the partial order relationship estimates be-
tween points in the image and propagates them to provide a
dense depth or reflectance map for the whole image, utilizing
priors specific to the task at hand.

We shall now describe the components of our frame-
work. We use the same architecture for both the tasks
demonstrated here (intrinsic image decomposition and
depth extraction), demonstrating its generality. We note,
however, that the framework is modular and individual
components can be independently adapted to the task at hand.

3.1. From input image to point pairs

We wish to choose \(N\) points from the image and an edge
structure \(E_{i,j}\) denoting which pairs of points \(i, j\) are to be
compared. Depth or reflectance discontinuities usually in-
duce changes in the measured intensity within the image,
creating strong gradients. The points we want to compare
need to be far away from such gradients so as to be centered
within relatively homogenous regions. The lines connecting
the points, however, should ideally cross such gradients, al-
lowing us to make the decision about the possible cause of
the observed change.
Figure 2: The points and edge structure extracted from a given image: a comparison is estimated on each edge. Note (a) that points rarely straddle strong edges and (b) the long range connectivity. (For this image we used a larger separation between the points for display purposes).

A simple way of finding points that satisfy the above requirements is to use the centers of superpixels [2]. Superpixels naturally follow gradients within images, so their centers tend to be locally far away from strong intensity changes. In order to choose edge structure connecting the points, we find for each point its adjacent neighbors in the superpixel segmentation. The first order neighbors often lie on opposing sides of strong gradients in the image. To allow for longer range interactions, we introduce connections between higher-order neighbors: we extract superpixels at several sizes, find their first order neighbors and snap this edge structure to the fine superpixel grid. See Figure 2 for an example of the resulting points and edge graph. Note that the superpixels are used only for their centers, and no segmentation information is utilized at this stage.

3.2. From point pairs to ordinal estimates

For each edge $E_{i,j}$ connecting points $i$ and $j$ in the image, we need to make a decision about the ordinal relationship between $i$ and $j$. This can be posed as a three way classification problem where the classes correspond to equality between the points, point $i$ being larger and point $j$ being larger. Here, the word “larger” has a natural interpretation according to the task: it means “darker” for intrinsic image decomposition, and “further away” for depth estimation, for example. Along with this estimate we would want an associated confidence value (namely, the normalized class probabilities).

We train a deep neural network to perform this classification. The network input is comprised of two different contexts: the first is the local appearance of the two points and their local surroundings, the second is a global context, which provides the network the overall image structure and the region of interest (ROI) in which the points reside. Specifically, for local context, we extract a patch around each point, their joint bounding box and provide the network with a mask denoting the points’ relative location within the bounding box. For global context, we input a downscaled version of the image, and a mask denoting the ROI: the location of the local context bounding box within the image. See Figure 3 for a depiction of the network input. The network architecture and training procedure are detailed in Section 4.

3.3. From ordinal to metric

The output of the deep network are 3 ordinal relationship probabilities for each pair of considered points. We need to propagate these estimates to all other points in the image, and move from ordinal estimates to metric. To achieve this, we must reconcile the ordering estimates for the points, some of which may be contradictory or ambiguous. Second, we need to find values for points which were not estimated, these are in fact the majority of pixels in the image. For the latter, we use superpixel segmentation and assume that the value throughout each superpixel is constant (yielding a piecewise constant solution in the resulting image). More sophisticated priors such as piecewise planar assumptions may be used [36], but we have found that as long as the superpixels are of small enough size, the constancy assumption gives good performance while speeding up inference.

Given this piecewise constancy assumption, we seek to find a global solution for the values of the points (denoted by $x_i$), while handling ambiguities in the orderings, incorporating the confidence of the classifier and respecting image information and problem scale. We pose this as a constrained quadratic optimization problem, which we explain...
below. We denote the equality decision using the super-
script or subscript $eq$, the first inequality decision (point $i$
being larger than point $j$) by $gt$ and the opposite inequality
decision by $lt$.

Our first term handles equality predictions. Since the
network predictions are uncertain, we do not want to use
hard constraints. Instead, for each edge $E_{i,j}$ we wish to
minimize the $L_2$ distance between the estimates of the corre-
spending points, weighted by the confidence of the equality
prediction $w_{ij}^{eq}$. We wish to minimize:

$$L_{eq}(x, R^{eq}) = \sum_{i,j} w_{ij}^{eq} (x_i - x_j - R_{ij}^{eq})^2$$  \hspace{1cm} (1)

w.r.t. $x$ and $R^{eq}$, where $R_{ij}^{eq} \sim \mathcal{N}(0, \sigma_{eq}^2)$ is a scalar
slack variable for the $ij$-th edge. The variance $\sigma_{eq}^2$ of
the normal distribution for $R^{eq}$ is computed from the statistics
of the training set. The above can be written in matrix form
as follows. Let $A_{eq} \in \mathbb{R}^{|E| \times N + |E|}$, where $|E|$ is the
number of edges, and $N$ the number of points. Each row of $A_{eq}$
has the entries $1, -1$ and $-1$ in the $i, j$ and $N + p$ columns,
respectively ($p$ is the index of $ij$ pair). The weights $w_{ij}^{eq}$
can be represented by a diagonal matrix $W_{eq} \in \mathbb{R}^{|E| \times |E|}$
in which the (diagonal) entries are $w_{ij}^{eq}$. Using this, Eq. 1
can be written in matrix form as:

$$L_{eq}(x, R^{eq}) = [x \ R^{eq}]^T A_{eq}^T W_{eq} A_{eq} [x \ R^{eq}]$$  \hspace{1cm} (2)

where $x \in \mathbb{R}^N$ and $R^{eq} \in \mathbb{R}^{|E|}$ are the variables $x_i$ and
$R_{ij}^{eq}$ respectively, stacked in vector form. For clarity, here
and subsequently $| R^{eq} |$ is a row vector.

Inequalities are handled in a similar manner. First, let us consider the inequalities corresponding to the prediction
that point $i$ is larger than point $j$. For each edge, we require the estimated difference to be some non negative number
$R_{ij}^{gt}$ such that:

$$L_{gt}(x, R^{gt}) = \sum_{i,j} w_{ij}^{gt} (x_i - x_j - R_{ij}^{gt})^2$$  \hspace{1cm} (3)

where $w_{ij}^{gt}$ is the associated confidence for this inequality
($x_i > x_j$), and $R_{ij}^{gt} \sim \mathcal{N}(\mu_{gt}, \sigma_{gt}^2)$ are the positive-valued slack
variables. Note that $\mu_{gt}$ is a positive value and that all
$R_{ij}^{gt}$ are constrained to be positive. Analogous to the equality
consitions Eq. 2, this can be written in matrix form, with a matrix $A_{gt}$ with entries in each row of value $1, -1$ and $-1$
and a diagonal weight matrix $W_{gt}$:

$$L_{gt}(x, R^{gt}) = [x \ R^{gt}]^T A_{gt}^T W_{gt} A_{gt} [x \ R^{gt}]$$  \hspace{1cm} (4)

Finally, we have a third term, $L_{lt}(x, R^{lt})$, for the inequality
$x_i < x_j$, with matrix $A_{lt} = -A_{gt}$, weights $W_{lt}$ and slack
variables $R^{lt}$.

In addition to the above terms, we also take into account the image structure. Specifically, we want to enforce
smoothness with respect to the image. This is achieved with an $L_2$ smoothness term between adjacent superpix-
els $m$ and $n$, weighted by local image gradients (calcu-
lated over the mean superpixel luminance $L$) such that

$$w_{m,n}^s = \exp(-\frac{1}{\rho} ||L_m - L_n||^2)$$

where $\rho$ controls the sen-
sitivity of the smoothness weights. For non-adjacent superpix-
els, $w_{m,n}^s = 0$. We use these weights in one of two ways.
First, we either directly smooth the values $x$, giving rise to
a smoothness term is of the form:

$$L_s(x) = \sum_{i,j} w_{ij}^s (x_i - x_j)^2 + \sum_i b_i x_i$$  \hspace{1cm} (5)

where the terms $b_i$ allow more flexibility in the choice of
smoothing (see Section 4 for an example). This can again be re-written in matrix form:

$$L_s(x) = x^T A_s^T W_s A_s x + x^T b_s.$$  \hspace{1cm} (6)

Combining all the above expressions, the resulting con-
strained quadratic problem is given by:

$$\min_{x, R^{eq}, R^{gt}, R^{lt}} \lambda_{eq} L_{eq}(x, R^{eq}) + \lambda_{gt} L_{gt}(x, R^{gt}) + \lambda_{lt} L_{lt}(x, R^{lt}) + \lambda_s L_s(x) + \sum_{ij} \left( \frac{(R_{ij}^{eq})^2}{\sigma_{eq}^2} + \frac{(R_{ij}^{gt} - \mu_{gt})^2}{\sigma_{gt}^2} + \frac{(R_{ij}^{lt} - \mu_{lt})^2}{\sigma_{lt}^2} \right)$$

s.t. $x > L, x < U, R^{eq} > 0, R^{gt} > 0, R^{lt} > 0$  \hspace{1cm} (7)

where the lower and upper bounds ($L$ and $U$) for $x$
are problem specific (e.g. $-\infty$ and 0 for log reflectance).
$\lambda_{eq}, \lambda_{gt}, \lambda_{lt},$ and $\lambda_s$ are weight parameters. Once we solve the
quadric system for the values of $x$, we floodfill each superpixel with the corresponding value, producing the final output
map.

4. Experiments

We use a common framework for both our mid-level
tasks: intrinsic image decomposition and depth estimation.
The differences in the two models are in the datasets and
some parameters, the details of which are given in subsequent sub-sections. The ability to use the same network
architecture and optimization model for both datasets is a
benefit of our ordinal framework. Furthermore, we can han-
dle images of any input size without rescaling, unlike many
other deep network based models.

For both models, we use a patch size of $16 \times 16$ pixels
around each point. The bounding box around the patches
is rescaled to $32 \times 32$ pixels. The location masks and ROI
are $32 \times 32$ pixels in size, and each mask is a Gaussian
blob around each of the points, with standard deviation $\sigma = 0.2$.
(in normalized 0-1 coordinates). The ROI is a rectangle at the bounding box location within the image, rescaled to the same size of the downscaled image. The image is always downscaled to be 64 × 64 pixels.

We train both the networks using the Caffe framework [16]. The network structure is depicted in Figure 4, having approximately 4 million parameters. Training was performed over 400,000 iterations with batch size 128. We start with a learning rate of 0.01 and reduce it every 30,000 iterations (with a reduction rate of 0.1). Momentum was 0.9 and weight decay 5 × 10^{-4}. We used an NVIDIA GeForce Titan X GPU, on which training takes approximately 10 hours.

4.1. Intrinsic image decomposition

We train our intrinsic image decomposition network on the Intrinsic Images in the Wild (IIW) dataset [5]. Each image in this dataset (5430 images in total) is associated with human annotations for selected pairs of points \((i, j)\). The annotators were asked the question “which of the two points have darker surface reflectance?” and provided one of three responses “i is darker than \(j\)” (\(gt\)), “i is lighter than \(j\)” (\(lt\)) or “Equal” (\(eq\)). We use these points and annotations as ground truth data for our network. Since the dataset is not split into train and test sets, we generate train, test and validation sets. The test and validation sets have 500 images each, and the rest of the images are put in the training set (4230 images). For each point pair, we extract patches around each point in the pair, location masks, a bounding box covering both patches, a region of interest (ROI) mask within the image and, finally, the downscaled image. Together, this forms the input to our network (see Figure 3).

After training, we solve for reflectance and shading for each image in the IIW test split. We assume grayscale shading and solve for scalar reflectance (as is done in [28, 5]). We use superpixels which are approximately 3% of the image width with long range connectivity (see Figure 2). Weights for the different terms are \(\lambda_{eq} = 5\), \(\lambda_{gt} = 1\), \(\lambda_{lt} = 1\) and \(\lambda_s = 0.5\). We set \(\sigma_{eq} = 0.001\), \(\sigma_{gt} = 0.001\) and \(\sigma_{lt} = 0.001\). We set \(\mu_{gt} = \log(2)\) and \(\mu_{lt} = \log(2)\). The smoothness term is applied to the log shading, that is, we smooth \(\log I_i - \log x_i\). This gives a non-zero \(b_3\) smoothness term in Eq. 7. Parameters were adjusted using the validation set. Since we solve for log reflectance values, the lower bound in Eq. 7 is set to \(-\infty\) and the upper bound to 0. After the solution is found we take the exponent of the result to obtain the final reflectance values (between 0 and 1).

For evaluation we follow the procedure introduced in [5] and use the Weighted Human Disagreement Rate (WHDR), the average disagreement rate with human annotators, weighted by their confidence:

\[
\text{WHDR}_\delta(\ell, x) = \frac{\sum_{ij} w_{ij} 1(\ell_{ij} \neq \tilde{\ell}_{ij, \delta}(x))}{\sum_{ij} w_{ij}} \tag{8}
\]

\[
\tilde{\ell}_{ij, \delta}(x) = \begin{cases} 
1 & \text{if } \frac{x_i}{x_j} > 1 + \delta \\
2 & \text{if } \frac{x_i}{x_j} > 1 + \delta \\
E & \text{else}
\end{cases} \tag{9}
\]

where \(x\) is the estimated reflectance map. \(\delta\) is the tolerance level (we use 0.1, as in [5]) and \(\ell_{ij}\) and \(w_{ij}\) are the ground truth human annotations and human confidence weights for the \(ij\)-th pair. Table 1 shows the performance for our framework, compared to a number of other state-of-the-art methods. We have used the results provided by [5] for comparison to other methods; the parameters for the competing methods were optimized with respect to the whole data set including the test images, while ours was fitted only on the train and validation sets. Note that our method significantly outperforms other methods, demonstrating more than a 10% relative decrease in error. Figure 5 shows the recovered reflectance/shading pairs for some images from the test set, along with the results of some of the other methods. Our recovered reflectance maps largely ignore illumination and texture related changes (such as the wooden cabinets and the ceilings).

4.2. Depth from single image

For depth recovery, we train our model on the NYU Depth v2 dataset [25]. Since we cannot directly train on the
metric estimates provided in the dataset, we have created a set of ordinal relationship annotations for it, analogous to the IIW dataset. For each image in the training set, we extract points and point pairs as described in Section 3. We set the ground truth label $\ell_{ij}$ for the $ij$-th pair as follows:

$$
\ell_{ij,\delta}(Z) = \begin{cases} 
1 & \text{if } \frac{Z_{ij}}{Z_{gt}} > 1 + \delta \\
2 & \text{if } \frac{Z_{ij}}{Z_{gt}} > 1 + \delta \\
E & \text{otherwise}
\end{cases}
$$

(10)

where $Z$ is the ground truth depth, and $\delta = 0.02$ is an empirically chosen threshold. After the annotated points and pairs are created, we extract local and global contexts from the RGB images. No metric information is provided during training.

After training, we solve for depth for each image in the NYU test set. We use superpixels which are approximately 3% of the image width with long-range connectivity. Weights for the different terms are $\lambda_{eq} = 1$, $\lambda_{gt} = 1$, $\lambda_{lt} = 1$, and $\lambda_s = 10$. We set the upper and lower bounds in Eq. 7 to 0 and 10. Unlike in the case of reflectance estimation, there is no constraint on the inequality magnitudes for depth differences. Therefore, we set a large variance for $\sigma_{gt} = 4$, $\sigma_{lt} = 4$, and set $\sigma_{eq} = 0.1$. The relatively larger value of $\lambda_s$ encourages the global solution to be smooth where the image is smooth.

We compare our metric results on the NYU test set, to that of [17, 3, 8]. The results on the standard benchmarks are reported in Table 2. We also compare our method with outputting just the mean over the training set, and using the mean as the prediction for any test image. The paper of [8] gives details on how the error measures are computed. Due to the specific nature of this dataset, the mean image (a cone of depth, depicted in the supplementary material) has reasonable performance.

Since our network was trained on ordinal measurements, we also introduce an ordinal error measure analogous to WHDR, (Eq. 8), which we dub WKDR (Weighted Kinect Disagreement Rate). WKDR is computed in exactly the same way as WHDR, but with the ground truth and recovered depths maps, from which labels are computed using Eq. 10. We compare our performance under this measure to that of [8], and the results are given in Table 3. Under this measure, our performance gap with [8] is considerably reduced. This suggests that with a different globalization method and more powerful priors, our metric performance on depth estimation could be improved.

In Figure 6, we show some example depth maps from our globalization, on images from the NYU dataset. In the grayscale depth maps, darker intensities are closer (smaller depth value) and lighter intensities are further. We note that we recover the overall subjective depth structure of the scene quite well, often with crisp edges at depth discontinuities.
Figure 6: Recovered depth from single images. From left to right: input image, our result, result of [8] and ground truth. While the results of [8] are qualitatively superior, our results do capture major structures of the image, and have crisper edges.

Figure 7: The results of the network analysis experiments: the left two columns measure the dependency of the networks’ output to local appearance differences. It can be seen that both networks are invariant to texture deformations (left column) such as blur and rotation. The reflectance network learns that a strong intensity difference means a reflectance change (a “Retinex”-like rule [18], with threshold of about 0.3), though it is sensitive to the polarity of the change. It also predicts that “red” hues are darker than than “green” and that saturated colors are darker than unsaturated, even though there is no intensity difference. Finally, on the right column we see the dependency of the network output as a function of relative distance and orientation of the patches. We see that both the depth and reflectance network have learnt that nearby points tend to be the same reflectance/depth. Additionally, the depth network learns that points closer to the bottom of the image tend to be closer, and that axis aligned pairs tend to be equal. The reflectance network does not show this behavior. See text for further details.

4.3. Network analysis

Deep networks have a large number of parameters, and often, understanding what they learn from data has proven to be challenging. Some recent progress has been made in this aspect [37]. While we can gain partial understanding by looking at learned filters and “network inversions”, another approach is to perform controlled experiments on the network outputs.

Our analysis is somewhat analogous to experiments in human psychophysics, where responses to controlled stim-


We refer the reader to [8] for details on the measure computation.


Table 2: Metric error measures on the NYU test set [25] (lower is better). Some error measures are not available for some of the methods. We present a set of experiments which


Table 3: Ordinal error measures on the NYU dataset (lower is better). On these measures, our method achieves competitive performance with [8] and significantly better than the mean image.


pairs of points in the tests, and plot the results as a function of relative orientation and distance. Results can be seen in Figure 7. While the reflectance network is largely invariant to orientation, the depth network learns two rules: the bottom point tends to be closer (a prior that has been used in the literature [19]) and points that are axis aligned (vertical or horizontal) tend to be at the same depth (which is a result of the indoor dataset we used, where walls and cabinets are ubiquitous). A final experiment is the dependence on the distance between the points: as expected, both network learn that nearby points tend to be equal, inline with widely employed smoothness priors.

4.4. Generalization

To test subjectively the generalization capability of the framework, we used images which are quite different from the training sets, such as close up objects and outdoor scenes. In Figure 8, we show our recovered reflectance and depth maps, and the depth map recovered by [8]. Since ground-truth depth and reflectance maps are not available for these images, no quantitative measure is available.

5. Discussion

We propose a framework that tackles mid-level vision problems by making ordinal decisions about points in an image. We demonstrate that such a system is able to provide good performance while still being interpretable. We are able to utilize the same framework for different modalities such as reflectance and depth. Since the output dimensionality of the classifier is tiny, a small set of “psychophysics” experiments sheds some light on the inner workings of the system. Globalizing these decisions allows to build a full metric explanation of the image to output reflectance, shading and depth maps. Future work will involve allowing different systems to interact to reinforce their decisions.

Input Image Our Depth Our Reflectance Depth [8]
References