Unsupervised CNN for Single View Depth Estimation: Geometry to the Rescue

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Abstract. A significant weakness of most current deep Convolutional Neural Networks is the need to train them using vast amounts of manually labelled data. In this work we propose a unsupervised framework to learn a deep convolutional neural network for single view depth prediction, without requiring a pre-training stage or annotated ground truth depths. We achieve this by training the network in a manner analogous to an autoencoder. At training time we consider a pair of images, source and target, with small, known camera motion between the two such as a stereo pair. We train the convolutional encoder for the task of predicting the depth map for the source image. To do so, we explicitly generate an inverse warp of the target image using the predicted depth and known inter-view displacement, to reconstruct the source image; the photometric error in the reconstruction is the reconstruction loss for the encoder. The acquisition of this training data is considerably simpler than for equivalent systems, requiring no manual annotation, nor calibration of depth sensor to camera. We show that our network trained on less than half of the KITTI dataset (without any further augmentation) gives comparable performance to that of the state of art supervised methods for single view depth estimation.

1 Introduction

The availability of very large human annotated datasets like Imagenet [4] has led to a surge of deep learning approaches successfully addressing various vision problems. Trained initially on tasks such as image classification, and fine-tuned to fit other tasks, supervised CNNs are now state of the art for object detection [11], per-pixel image classification [19], depth and normal prediction from single image [15], human pose estimation [7] and many other applications. A significant and abiding weakness, however, is the need to accrue labeled data for the supervised learning. Providing per-pixel segmentation masks on large datasets like CoCo [16], or classification labels for Imagenet requires significant human effort and is prone to error. Supervised training for single view depth estimation for outdoor scenes requires expensive hardware and careful acquisition. For example, despite using state of art 3D sensors, multiple calibrated cameras and inertial sensors, a dataset like KITTI [10] provides sparse depth maps with less
We propose a stereopsis based auto-encoder setup: the encoder (Part 1) is a traditional convolutional neural network with stacked convolutions and pooling layers (See figure 2) and maps the left image \( I_1 \) of the rectified stereo pair into its depth map. Our decoder (Part 2) explicitly forces the encoder output to be disparities (scaled inverse depth) by synthesising a backward warp image \( I_w \) by moving pixels from right image \( I_2 \) along the scanline. We use the reconstructed output \( I_w \) to be matched with the encoder input (Part 3) via a simple loss. For end-to-end training, we minimize the reconstruction loss with a simple smoothness prior on disparities which deals with aperture problem, while at test time our CNN performs single-view disparity (inverse depth) prediction, up to the scene scale given in form of \( fB \) at the time of training.

than 5% density on the captured image resolutions and with only a limited reliable depth range. A significant challenge now is to develop unsupervised training regimes that can train networks that perform either as well as, or better than those trained used using these supervised methods. This will be a major step towards realizing in-situ learning, in which we can retrain or tune a network for specific circumstances, and towards life-long learning, in which continuous acquisition of data leads to improved performance over time.

In this paper we are particularly concerned with the task of single-view depth estimation, in which the goal is to learn a non linear prediction function which maps an image to a (scaled) depth map of the scene. CNNs have achieved the state-of-the-art performance on this task due to their ability to capture the complex and implicit relationships between scene depth and the corresponding image textures, scene semantics, and local and global context in the image. State-of-the-art supervised learning methods for this task train a CNN to minimize a loss based on either the scale invariant RMS [6], or the log RMS [17] of the depth predictions from ground truth. These networks have been trained using datasets that provide both RGB images and corresponding depth maps such as NYUv2 and KITTI.

However as noted in [17], the networks learnt by these systems do not generalise well outside their immediate domain of application. For example,
trained two separate networks, one for indoors (using NYUv2) and one for street scenes (using KITTI), because the weights learnt in one do not work well in the other. To transfer the idea of single-view depth estimation into yet another domain would require indulging in the expensive task of acquiring a new RGB-D dataset with well-aligned image and depth values, and re-train the network. An alternative to this would be to generate a large synthetic or semi-synthetic dataset using graphical rendering, an approach that has met with some success in [12]. However it is difficult to capture the full variability of real-world images in such datasets.

Another possible approach would be to capture a large dataset of stereo images, and use standard geometric methods to compute the disparity map for each pair, yielding a large set of image-plus-disparity-map pairs. We could then train a network to predict a disparity map from a single view. However such a system will likely learn the systematic errors in estimated depths, “baking in” the failure modes of the stereo algorithm. Factors such as sensor flare, motion blur, lighting changes, shadows, etc are present in real images and rarely dealt with adequately by standard stereo algorithms.

We adopt a different approach that moves towards a system capable of in-situ training or even lifelong learning, using real un-annotated imagery. We take inspiration from the idea of autoencoders, and leverage well-understood ideas in visual geometry. The result is a convolutional neural network for single-view depth estimation, the first of its kind that can be trained end-to-end from scratch, in a fully unsupervised fashion, simply using data captured using a stereo rig.

2 Approach

In this section we give more detail of our approach. Figure 1 explains our idea graphically. To train our network we make use of pairs of images with a known camera motion between the two, such as stereo pairs. Such data are considerably more easily acquired than calibrated depth maps and aligned images. In our case we use large numbers of stereo pairs, but the method applies equally to data acquired from a moving SLAM system in an otherwise static scene.

We learn a CNN to model the complex non-linear transformation which converts the image to a depth-map. The loss we use for learning this CNN is the photometric difference between the input – or source – image, and the inverse-warped target image (the other image in the stereo pair). This loss is both differentiable (to facilitate back-propagation) and is highly correlated with the prediction error - i.e. can be used to accurately rank two different depth-maps without using groundtruth labels.

This approach can be interpreted in the context of convolutional autoencoders. The task in a standard autoencoder is to encode the input with a series of non-linear operations to a compressed code that captures sufficient core information so that a decoder can reconstruct the input with minimal reconstruction error. In our case we replace the decoder with a standard geometric image warp, based on the predicted depth map and the relative camera positions. This has
two advantages: first, the decoder in our case does not need to be learnt, since it is already a well-understood geometric operation; second, our reconstruction loss naturally encourages the code to be the correct depth image.

2.1 Our autoencoder loss

Every training instance \( i \in \{1 \cdots N\} \) in our setup is a rectified stereo pair \( \{I_1, I_2\} \) captured by a single pre-calibrated stereo rig with two cameras having focal length \( f \) each which are separated horizontally by a distance \( B \). Assuming that the predicted depth of a pixel \( x \) for the left image of the rig via CNN is \( d_i(x) \), the motion of the pixel along the scan-line \( D_i(x) \) is then \( fB/d_i(x) \). Thus, using the right image \( I_2 \), a warp \( I_w \) can be synthesized as \( I_2(x + fB/d_i(x)) \).

With this explicit parameterization of the warp, we propose to minimize standard color constancy (photometric) error between the reconstructed image \( I_w \) and the left image \( I_1 \):

\[
E_{i\text{recons}} = \int_\Omega \| I_w(x) - I_1(x) \|^2 dx = \int_\Omega \| I_2(x + \underbrace{D_i(x)}_{fB/d_i(x)}) - I_1(x) \|^2 dx \tag{1}
\]

It is well known that this photometric loss function is non-informative in homogeneous regions of the scene. Thus multiple disparities can generate equally good warp \( I_w \) and a prior on the disparities is needed to get a unique depthmap. We use very simple \( L^2 \) regularization on the depth discontinuities as our prior to deal with the aperture problem:

\[
E_{i\text{smooth}} = \| \nabla D_i(x) \|^2 \tag{2}
\]

This regularizer is known to over-smooth the estimated motion, however a vast literature of more sophisticated edge preserving regularizers with robust penalty functions like \[2,22\] for which gradients can be computed are at our disposal and can be easily used with our setup to get sharper depth maps. As the main purpose of our work is to prove that end to end training of the proposed autoencoder is feasible and helpful for depth prediction, we choose to minimize the simplest suitable loss summed over all training instances:

\[
E = \sum_{i=1}^{N} E_{i\text{recons}} + \gamma E_{i\text{smooth}} \tag{3}
\]

where \( \gamma \) is the strength of the regularization forcing the estimated depth maps to be smooth.

Our loss function is described in \[3\] for every frame is similar to the standard Horn and Schunck optic flow cost \[13\]. However, the major difference is that our disparity maps \( D_i \)'s are parametrized to be a non-linear function of the

\[^1\text{All training images are assumed to be taken with a fixed rectified stereo setup as is the case in KITTI for simplicity but our method is generalizable to work with instances taken by different calibrated stereos.}\]
We adapt the convolution based upsampling architecture proposed in [18] to mimic the coarse to fine stereo estimations. Our upsampling filter is initialized with simple bilinear interpolation kernel and we initialize the corresponding pooling layer contribution by setting both bias and 1x1 convolution filter to be zero. The figure shows how features coming from previous layers of the CNN ($L_3$) combined with finer resolution loss function generates better depth maps at $46 \times 154$ from our bilinear upsampled initial estimate of coarser prediction at $22 \times 76$.

input image and unknown weights of the CNN which are shared for estimating the motion between every stereo pair. This parameter sharing enforces consistency in the estimated depths over 1000’s of correlated training images of a large dataset like KITTI. Our autoencoder’s reconstruction loss can be seen as a major generalization of the multiframe optic flow methods like [9,8]. The difference is, instead of modeling the correlations in the estimated motions for a shorter video sequence with a predefined linear subspace [8], our autoencoder learns (and models) valid flows which are consistent throughout the dataset non-linearly.

3 Coarse to fine training with skip architecture

To compute the gradient for standard back-propagation on our cost (1), we need to linearize the warp image at the current estimate of the depths using taylor expansion:

$$I_2(x + D^{n+1}(x)) = I_2(x + D^n(x)) + (D^{n+1}(x) - D^n(x))I_{2h}(x + D^n(x))$$ (4)

where $I_{2h}$ represents the horizontal gradient of the warp image computed at the current disparity. This linearization is valid only for small values of $D^{n+1}(x) - \ldots$
Fig. 3. Network architecture: The blocks C (red), P (yellow), L (dark blue), F (green), D (blue) correspond to convolution, pooling, local response normalization, FCN and upsampling layers respectively. The FCN blocks F1 and F2 combine the predictions from upsampling layers (L8 and L9) and the output pooling layers P4 and P3 (L4 and L5) respectively. The information from the encoding layers L4 and L5 contain local appearance information such as textures, edges and help to sharpen the predicted depthmap.

$D^n(x)$ limiting the magnitude of estimated disparities in the image. To estimate larger motions (smaller depths) accurately, a coarse to fine strategy with iterative warping is well established in the stereo and optic flow literature which facilitates gradient decent based continuous optimization.

However, our disparities are a non-linear function of the CNN parameters and the input image. To move from coarse to fine level, we not only need a good depth initialization at the finer resolutions to linearize the warps but also the corresponding CNN parameters which predict these initial depth maps for each training instance. Thankfully recent fully convolutional architecture with upsampling proposed in [18] is appropriate choice simulate coarse to fine warping for our system. As depicted in Figure 2, given a networks which predict $M \times N$ depth map we can use a simple bilinear upsampling filter, to initialize upscaled depths (to get $2M \times 2N$ depth maps) keeping the other network parameters fixed. It has been shown that the finer details of the images are captured in the previous layers of CNN and fusing back such information is helpful for refining a coarse CNN prediction. We use a simple $1 \times 1$ convolution with the filter and bias both initialized to zero and simply use the convolved image output to upscaled coarse depth.

4 Our Network Architecture

The network architecture for our deep convolutional encoder is shown in figure 4 which is similar to the alexnet architecture [14] upto C5 layer. We replace
the fully connected layer of alexnet by a fully convolutional layer with 2048 convolution filters of size $5 \times 5$ each.\footnote{A $5 \times 18$ convolution can be used instead to increase network capacity and replicate the effect of a fully connected layer of [14].} This reduces the number of parameters in the network and allows for the network to accept variable size inputs during testing. More importantly, it preserves the spatial information present in the image and allows us to upsample the predictions in a stage-wise manner in the layers that follow the L7 output of the figure, which is a requirement for our stereopsis based auto encoder as explained in section 3. Inspired from the observations from [18], that the finer details in the images are lost in the last few layers of the deep convolutional network we employ the “skip architecture” that combines the coarser depth prediction with the local image information to get crisper finer predictions. The affect of which is illustrated using a example from validation set in figure 2. The layers following the $L7$ output (a coarse $5 \times 18$ depth map) in our network are all upsampling layers each converting a coarser low resolution depth map to a higher resolution output as explained in section 3.

5 Experiments

We evaluate our method on publicly available KITTI dataset \cite{10} that consists several outdoor scenes captured using a stereo camera mounted on a moving vehicle. We employ the same train/test split used in \cite{6}: From the 56 scenes belonging to the categories “city”, “residential” and “road”, we choose 28 for training and remaining 28 for testing. We downsample the left images by a factor of 2 to bring it to 188 x 620 and use it as input to the network. Corresponding right images in the stereo pairs are used at the resolutions of predicted depth maps at every stage of our our coarse to fine training to generate the warp and match it with resized left image.

The training set consists of 23488 stereo pairs out of which we use 22600 for training and remaining for validation. Neither the right to left stereo nor any data augmentation is used. For testing, we use the 697 images provided by \cite{6} from the testset. We do not use any groundtruth depths for training the network. To evaluate all the results produced by our network we use simple upscaling of the low resolution disparity predictions to the resolution at which the stereo images were captured by the KITTI. Using stereo baseline of 0.64 meters as reported in KITTI, we convert the upsampled disparities to the depth for evaluation. We evaluate our method using the error measures reported in \cite{6,17}:

\[
\text{RMS: } \sqrt{\frac{1}{T} \sum_{i \in T} \|d_i - d_i^{gt}\|^2} \quad \text{log RMS: } \sqrt{\frac{1}{T} \sum_{i \in T} \|\log(d_i) - \log(d_i^{gt})\|^2}
\]

\[
\text{abs. relative: } \frac{1}{T} \sum_{i \in T} \frac{|d_i - d_i^{gt}|}{d_i^{gt}} \quad \text{sq. relative: } \sqrt{\frac{1}{T} \sum_{i \in T} \frac{\|d_i - d_i^{gt}\|^2}{d_i^{gt}}}
\]

\[
\text{Threshold % of } d_i \text{ s.t. } \max\left(\frac{d_i}{d_i^{gt}}, \frac{d_i^{gt}}{d_i}\right) = \delta < \text{thr}
\]
5.1 Implementation Details

We train our network using the CNN toolbox MatConvnet [21]. We use SGD for optimization with momentum 0.9 and weight decay of 0.0005. It is important to note that our network weights starts with a random initialization of the first 5 layers of the alexnet and we append the $5 \times 5$ fully convolutional layer initialized with zero weights to get zero disparity estimates. Due to the linearization of the loss function as explained in section 3, we learn the network proposed in Figure 4 in multiple stages, starting from the coarsest level (5x18 depthmaps), and iteratively adding upsampling layer at a time.

The learning rate for the network which predicts depths at the coarsest resolution is initially set to 0.01 and gradually decreased after each epoch using the factor $1/(1 + \alpha \cdot n)^{(n-1)}$ where $n$ is the index of current epoch and $\alpha = 0.0005$. We set the number of epochs to 100 for learning depths for pyramid level in the coarse to fine fashion. Since the number of pixels increase by a factor of 4 (with 2× upsampling of the depthmaps), the cost approximately increases by the same factor at every finer level. Hence we decrease the initial learning rate by a factor of 4 for the subsequent layers. The smoothness prior strength $\gamma$ was set to 0.01.

### Table 1. Comparison with state-of-the-art methods on KITTI dataset.

| Methods      | Resolution | RMS  | log RMS | abs. relative | sq. relative | $\delta < 1.25$ | $\delta < 1.25^2$ | $\delta < 1.25^3$ |
|--------------|------------|------|---------|---------------|--------------|-----------------|------------------|------------------|
| Ours L9      | 22×76      | 5.722| 0.314   | 0.210         | 1.368        | 0.654           | 0.871            | 0.947            |
| Ours L10$^1$ | 46×154     | 5.836| 0.342   | 0.254         | 1.715        | 0.601           | 0.839            | 0.936            |
| Ours L10$^2$ | 46×154     | 5.461| 0.304   | 0.207         | 1.347        | 0.678           | 0.883            | 0.952            |
| Ours L11     | 94×310     | 5.422| 0.297   | 0.198         | 1.328        | 0.701           | 0.888            | 0.953            |
| Mean         | -          | 9.635| 0.444   | 0.412         | 5.712        | 0.556           | 0.752            | 0.870            |
| Make3D [20]  | Dense      | 8.734| 0.361   | 0.280         | 3.012        | 0.601           | 0.820            | 0.926            |
| Eigen etal (c) [6] | 28×144 | 7.216| 0.273   | 0.194         | 1.531        | 0.679           | 0.897            | 0.967            |
| Eigen etal (f) [6] | 27×142 | 7.156| 0.270   | 0.190         | 1.515        | 0.692           | 0.899            | 0.967            |
| Fayao etal (pt) [17] | superpix | 7.421| -       | -             | -            | 0.613           | 0.858            | 0.949            |
| Fayao etal (ft) [17] | superpix | 7.046| -       | -             | -            | 0.656           | 0.881            | 0.958            |

5.2 Effect of upsampling

For learning the upsampling layers, we start with the coarsest layer of $5 \times 18$ resolution (L7) and progressively add upsampling layers L8, L9, L10, and L11 whose resolutions are $10 \times 37$, $22 \times 76$, $46 \times 154$ and $94 \times 310$ respectively. While adding upsampling layers, we crop and pad the layers such that the resolution of upsampling matches with the resolution of the maps from the pooling layers P4 and P3. Row 1 and 2 of our table correspond to our L9 and L10 output.

$^1$ Layer 10 obtained by combining upsampling and pooling layer output P2  
$^2$ c and f indicates the the coarse and fine networks of [6]  
$^3$ pt and ft indicates the the pre-train and fine-tuned networks of [17]
with 2 and 3 upsampling layers with corresponding pooling layer contributing to the finer depth prediction. Consistent with [18] we also observe that after 2 upsampling layers, skipped architecture starts to give diminishing results. We believe that this is due to the fact that the first few layers of CNN are more closer to images then depth and a simple linear combination of the these layers features with that of the coarse depth map does not work well. However higher resolution images still have very fine scale information which can be back-propagated via out loss function. As evident from the third rows in table 1 layer L10 without adding pooling layer output P2 outperforms the counterparts thus for further refinements, we only use a upsampling without any pool layer input.

5.3 Comparison with State-of-the-art Methods on KITTI Dataset

In table 1 we compare the performance our method with state-of-the-art methods [20,6,17]. We propose to simply upscale all our predicted disparities to the size of the KITTI images and use the relation \( d = \frac{fB}{D} \) to compute the depths \( d \) from the disparities \( D \). Errors for other methods are taken from [6,17]. For fair comparison we evaluate our results on the same cropped region of interest as [6]. Since the supervised methods are trained using the groundtruth depth that ranges between 1 and 50 meters whereas we predict large depths, for fair evaluation we clamp the predicted depth values for our method between 1 and 50 for evaluation, i.e. setting the depths bigger then 50 meter to 50.

Our method achieves the lowest RMS and sq. relative error on the dataset and significantly outperforms other methods for these measures. It performs on par with the state-of-the-art methods on other evaluation measures. Eigen et al [6] obtains lower error in terms of log RMS compared to ours. This is because log RMS is biased towards higher depth errors. Besides, supervised methods being trained with log or scale invariant depth error measures are bound to perform well on similarly biased evaluation criteria. In addition, the number of parameters in our network (15M) is significantly lesser compared to [6] (90M) and marginally lesser than [6] (20M).

The most noteworthy point is that ours is completely unsupervised method trained with randomly initialize the weights of the network, whereas [6] and [17] initialize the network using alex-net and VGG-16 respectively and are supervised.

Figure 5.1 compares the output inverse depth maps (scaled to [0 1]) for the L9 (2\textsuperscript{nd} column) and L11 (3\textsuperscript{rd} column) layers of the proposed method and [6]. We appropriately pad the predictions provided by the authors of [6] to generate the visualizations of [6] at the correct scale. It is evident from the figure that both L9 and L11 are able to capture objects that are closer to the camera with significantly more details. Edges are localized more accurately in L11 results compared to L9. This clearly depicts that even with the simple linear interpolation of the coarse depth estimation, the finer alignment errors are correctly back-propagated leading to the performance boost.

In summery, our simple, skinnier network with less then half of the training images used by [6] gives on par results without any supervision which looks
visually more appealing and should be refined with small changes like using better loss functions, replacing linear interpolation filter with a learned polynomial filter. As our method is completely unsupervised, it can be trained on theoretically limitless data with more deeper networks to capture variation and give depthmaps at image resolutions.

6 Related work

In this work we have proposed a geometry inspired unsupervised setup for visual learning, in particular addressing the problem of single view depth estimation. Our main objective was to address the downsides of training deep networks with large amount of labeled data. Another regime of works which attempts to address this issue are the set of methods like [12,5] which rely mainly on generating synthetic/semi-synthetic training data with the aim to mimic the real world and use it to train deep network in a supervised fashion. For example, In [5], CNN is used to discriminate a set of surrogate classes where the data for each class is generated automatically from unlabeled images. The network thus learned is shown to perform well on the task image classification. Or Handa etal [12] learn a network for semantic segmentation using synthetic data of indoor scenes and show that the network can generalize well on the real-world scenes.

Methods which do stereo with CNN: Recently, many methods have used CNN to learn good visual features for matching patches which are sampled from the stereo dataset like KITTI [23,3] and match these features while doing classical stereo to get state of the art depth estimation. These methods are relying on local matching and lose the global information about the scene and use ground truth. But their success is already an indicator that a joint visual learning and depth estimation approach like ours could be extended at the test time to use a pair of images.

Using camera motion as the information for visual learning is also explored in the works like [1] which directly regress over the 6DOF camera poses to learn a deep network which performs well on various visual tasks. In contrast to that work, we train our CNN for a more generic task of synthesizing image and get the state of art single view depth estimation as a bonus. [1] suggests that geometry can help in learning good visual features and it will be of immense interest to evaluate the quality of the visual features learned with our framework.

7 Conclusions

In spite of the enormous growth and success of deep neural networks for a variety of visual tasks, an abiding weakness is the need for vast amounts of annotated training data. We are motivated by the desire to build systems that can be trained relatively cheaply without the need for costly manual labelling or even trained on the fly.

To this end we have presented the first convolutional neural network for single-view depth estimation that can be trained end-to-end from scratch, in a
fully unsupervised fashion, simply using data captured using a stereo rig. We have shown that our network trained on less than half of the KITTI dataset (without any further augmentation) gives comparable performance to the current state of art supervised methods for single view depth estimation.

Various natural extensions to our work present themselves. We have yet to explore the full capacity of our network. Instead of training on KITTI data (which is nevertheless convenient because it provides a clear baseline) we aim to train on a continuous feed from a stereo rig “in the wild”, and to explore the effect on accuracy by augmenting the KITTI data with new stereo pairs. Furthermore, as intimated in the Introduction, our method is not restricted to stereo pairs, and a natural extension is to use a monocular SLAM system to compute camera motion, and use this known motion within our autoencoder framework; here the warp function is slightly more complex than for rectified stereo, but still well understood. The resulting single-view depth estimation system could be used for bootstrapping structure, or generating useful priors on the scene structure that capture much richer information than typical continuity or smoothness assumptions. It also seems likely that the low-level features learned by our system will prove effective for other tasks such as classification, in a manner analogous to [15], but this hypothesis remains to be proven experimentally.
**Fig. 4.** Inverse Depths visualizations. Brighter color means closer pixel.

| Input Image | Coarse Results | Upsampled Results | Eigen et al |
|-------------|----------------|-------------------|-------------|
| ![Input Image](image1.png) | ![Coarse Results](image2.png) | ![Upsampled Results](image3.png) | ![Eigen et al](image4.png) |
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