Abstract

Deep learning applied to the reconstruction of 3D shapes has seen growing interest. A popular approach to 3D reconstruction and generation in recent years has been the CNN encoder-decoder model usually applied in voxel space. However, this often scales very poorly with the resolution limiting the effectiveness of these models. Several sophisticated alternatives for decoding to 3D shapes have been proposed typically relying on complex deep learning architectures for the decoder model. In this work, we show that this additional complexity is not necessary, and that we can actually obtain high quality 3D reconstruction using a linear decoder, obtained from principal component analysis on the signed distance function (SDF) of the surface. This approach allows easily scaling to larger resolutions. We show in multiple experiments that our approach is competitive with state-of-the-art methods. It also allows the decoder to be fine-tuned on the target task using a loss designed specifically for SDF transforms, obtaining further gains.

1 Introduction

In recent years, we have witnessed an increased interest in extending the successes of deep learning to the analysis and representation of 3D shapes. This includes long standing problems, such as 3D shape reconstruction from single or multiple views [8, 32], shape from silhouettes [7], shape from contours [2], and shape completion [21]. Solutions to these problems can have a significant impact to applications in robotics [3], surgery [20], and augmented reality [14].

One of the preferred categories of models for tackling these problems is the CNN encoder-decoder architecture [8], popularized originally in the context of segmentation [5, 19]. For example, in the single view reconstruction task a 2D CNN will encode the 2-D image and a 3D CNN decoder model will produce the final representation in voxels. Standard decoders, however, are ineffective in larger resolutions and do not make full use of the structure of the object. Similar problems arise in more general attempts to learn latent variable models of 3D
More recently authors have considered alternative representations of shapes to a standard 3D discretized set of voxels [8, 12, 32, 34, 35], one that can permit more efficient learning and generation. These include point clouds [10], meshes [13, 31], and signed distance transform based representations [22, 23]. To date there is not an agreed upon canonical 3-D shape representation for use with deep learning models nor a canonical decoder architecture for use with any of the described shape representations. Indeed, many complex alternative decoder architectures have been used [25, 29]. In this work, we ask whether a very simple decoder architecture matched with the right shape representation can yield strong results. Building on the recent use of the Signed Distance Function (SDF) in shape representation we demonstrate a simple latent shape representation that can be used in downstream tasks and easily decoded. More specifically, in this work, we consider a latent shape representation obtained by applying PCA on the SDF transformed shape. We show this leads to a latent shape representation that can be used directly in downstream tasks like 3D shape reconstruction from a single view and 3D shape completion from a point cloud.

Our work a) reinforces the relevance of SDF as a representation for 3D deep learning; and b) demonstrates that a simple representation obtained by applying PCA on the SDF transform can lead to an effective latent shape representation. This representation allows for results competitive to state of the art in standard benchmarks. Our work also suggests more complex benchmarks than the current ones may be needed to push forward the study of learned 3D shape reconstruction.

The paper is structured as follows. In Sec. 2 we discuss the related work. We outline the basic methods used in the experiments in Sec. 3. We show extensive quantitative and experimental results comparing our approach to existing methods in Sec. 4.
Our work can also be seen as complementary to the very recent observations in Tatarchenko et al. [30] which highlights that good 3D single view reconstruction performance can be achieved by using retrieval or clustering methods. We note, however, that the descriptors used in that work are more complex.

PCA has been classically used to represent shapes in a variety of contexts. For example, classical methods in computer vision such as the active appearance model Edwards et al. [9] and the 3D morphable model used in face analysis Blanz et al. [1] are based on PCA shape representations. However, these typically are applied in a different context requiring transforming the shape to a reference set of points and applying PCA on the coordinates. Leventon et al. [17] used signed distance functions to embed 2D curves applying PCA to obtain statistical models. To the best of our knowledge it has not been combined with the SDF representing a surface in 3D. We note that level set methods and the SDF have only recently been revisited as an effective representation that can be combined with 3D deep learning [6, 22, 23]. Moreover, it is enlightening that this classic approach to shape representation can be competitive with deep learning methods on standard benchmarks.

3 Methods

In this section, we start with reviewing the SDF transform and then describe our simple yet effective approach to shape representation.

3.1 Signed Distance Functions

Consider a 3D shape and its closed surface $\Gamma \subset \mathbb{R}^3$. The Signed Distance Function (SDF) of $\Gamma$ is a mapping $\phi : \mathbb{R}^3 \mapsto \mathbb{R}$ from any point $x \in \mathbb{R}^3$ to the surface:

$$\phi(x) = \pm \inf_{y \in \Gamma} \|x - y\|,$$

with the convention that $\phi(x)$ is positive on the interior and negative on the exterior of $\Gamma$.

In Michalkiewicz et al. [22] a CNN decoder model is used to predict the SDF representation from a latent space as well as to learn autoencoders. We note, however, that this representation is well structured and objects are often grouped by category, we thus ask if a much simpler linear and non-convolutional decoder model can be effective at capturing its variability, leading to the $\text{eigenSDF}$ representation described in the next section.

The above paper [22] further considers a loss function for the SDF representation that approximately minimizes the point-wise distance:

$$L_\varepsilon(\theta) = \left( \sum_{x \in \Omega} \delta_\varepsilon(\hat{\phi}^j(x))d^j(x) \right)^{1/p} + \alpha \sum_{x \in \Omega} (\|\nabla \hat{\phi}^j(x)\| - 1)^2$$

with $\theta$ being parameters of the network, $\alpha$ a weighting factor, $\Omega$ an equidistant grid on which $\phi$ is evaluated, $\delta_\varepsilon$ approximated Dirac delta, $\hat{\phi}$ inferred Signed Distance Function, and $d(x)$ the closest distance between grid point $x$ and the ground truth shape. We will use this loss function to fine-tune our decoder model in the sequel.
3.2 EigenSDF

We apply the PCA transform to $\phi_{all} = \{\phi_i\}_{i=1..N}$, with $N$ being the number of training examples. The eigenvectors $E$ have the shape of $(k, M^3)$ with $M$ being the grid resolution and $k$ being the number of used eigenvectors. We project each SDF $\phi$ to the latent representation $\phi_c$ using the eigenvectors $E$: $\phi_c = \phi E^T$. Here, $\phi_c$ has a shape of $(1, k)$. In the sequel, we will denote this representation as the eigenSDF. Note that applying PCA to the naive voxel representation would be inappropriate as the data is binary and therefore ill-suited for linear subspace methods such as PCA.

For downstream tasks we predict directly the latent representation $\phi_c$. We will also consider using $E$ as an initialization which is finetuned by training on the SDF shape representation directly using Eq. 2. A high level overview of our framework is given in Figure 1.

4 Experiments

We evaluate the proposed representations on 3 tasks: i) 3D reconstruction; ii) 3D reconstruction from point cloud; and iii) 3D reconstruction with autoencoders.

These applications are evaluated on 13 categories from the ShapeNet repository [4].

Preprocessing. In order to work on SDFs, we need to have a well defined interior and exterior of an object. We first preprocess the meshes to make them watertight using the method proposed in [27]. Following common practice, we render each ground truth mesh
into 24 2D views using equally spaced azimuth angles. For each ground truth mesh, we compute a corresponding SDF in a $128 \times 128 \times 128$ discretized voxel grid.

**Metrics.** Following the [21] experimental setup, we report 3 metrics. The first one is Intersection over Union (IoU), also known as Jaccard Index, between ground truth shape $S$ and prediction $\tilde{S}$:

$$\text{IoU} = \frac{|S \cap \tilde{S}|}{|S \cup \tilde{S}|}.$$  

The second metric measures point-wise distance between ground truth point set $S_P$ and prediction $\tilde{S}_Q$ using the symmetric Chamfer distance:

$$\text{chamfer}(S_P, \tilde{S}_Q) = \frac{1}{2|P|} \sum_{p \in P} \min_{q \in Q} |p - q| + \frac{1}{2|Q|} \sum_{q \in Q} \min_{p \in P} |p - q|.$$  

Finally, we measure the angular distance using normal consistency (nc) metric:

$$\text{nc}(S_P, \tilde{S}_Q) = \frac{1}{2|P|} \sum_{p \in P} |N_{S_P}(p) \cdot N_{\tilde{S}_Q}(n_{\tilde{S}_Q}(p))| + \frac{1}{2|Q|} \sum_{q \in Q} |N_{\tilde{S}_Q}(q) \cdot N_{S_P}(n_{S_P}(q))|,$$

where $N_S(p)$ denotes normal of point $p$ lying on surface $S$ and $n_S(q)$ denotes nearest neighbour of point $q$ lying on surface $S$.

### 4.1 3D Reconstruction from Single 2D View

In this set of experiments, we evaluate the eigenSDF approach described in Sec 3. We perform PCA jointly on all categories using a starting resolution of $128 \times 128 \times 128$. For memory efficiency, we use incremental PCA [26]. $k$ eigenvectors were chosen to capture at least 99.5% of the variance within the dataset. The image encoder is a 2D CNN whose architecture is taken from [25]. We minimize the $\ell_2$ loss between the SDF projected into the latent space $\phi$, and the prediction of the 2D CNN. This network is trained for 100 epochs using an ADAM [15] optimizer. Initial learning rate was set to $10^{-3}$ and dropped at epoch 30 to $10^{-4}$. Furthermore, we consider finetuning the representation starting with the eigenvectors from PCA and using Eq 2. This baseline is referred to as eigenSDF (finetuned).

In order to demonstrate that a gain is made by PCA versus just architecture, we also train a linear autoencoder of the same size ($M \times k$) and finetune it with Eq 2. This baseline is referred to as linearSDF and linearSDF(finetuned).

Complete results are given in Table 1. First, we observe that simply using a same sized linear model linearSDF (finetuned) is outperformed by using the eigenSDF. Compared to alternatives, our method gives more significant gains in Chamfer metric than all competitors and can be further improved with the finetuning. We also observe improvements in the normal consistency metric. For the IoU metric, we observe that eigenSDF outperforms all methods except Mescheder et al. [21]. Note that according to Sun et al. [28] Chamfer distance is a far better metric for shape comparison than IoU.
## 4.2 3D Shape Completion from Point Clouds

We next consider shape completion from a point cloud. This task has been studied in [18, 21]. Similar to experimental setup of [21], we use 13 categories from ShapeNet repository and we pre-process the meshes to make them watertight. We randomly sample 300 points from ground truth meshes and add a Gaussian noise with 0 mean and 0.05 standard deviation. The same metrics have been used as described in section 4.1.
We have encoded the input point cloud with PointNet encoder with a bottleneck dimension of 512 \cite{24} and decoded it with linear decoder from section 4.1. A similar set of baselines has been used as in the previous section and compared to \textit{eigenSDF}. We observe similar large gains in the Chamfer metric and competitive performance in other metrics. Results in Table 2 show that, similar to 3D reconstruction task, our performance is much better in Chamfer distance, similar in normal consistency, and the second best in IoU.

| method          | IoU↑ | Chamfer ↓ | nc ↑ |
|-----------------|------|-----------|------|
| \textit{eigenSDF} (ours) | 0.568 | 0.077 | 0.852 |
| 3D-R2N2 ([24]) | 0.565 | 0.169 | 0.719 |
| PSGN ([24])     | -    | 0.144 | -    |
| DMC ([24])      | 0.674 | 0.117 | 0.848 |
| ONet ([24])     | 0.778 | 0.079 | 0.895 |

Table 2: Results on 3D shape completion

4.3 3D Reconstruction from Latents

Finally, we consider a simple 3D reconstruction task \cite{24}. This can also be viewed as measuring the representational power of the model \cite{21}. We evaluate reconstruction quality of \textit{eigenSDF} versus other methods, particularly CNN-based autoencoders. The goal is to reconstruct test set shapes. An initial resolution of \(128 \times 128 \times 128\) was used and reduced to \(k = 512\) as done in other works \cite{21}. We use \textit{cars} category from ShapeNet repository and evaluate reconstruction on unseen data. For the evaluations, in addition to the metrics used in section 4.1, we further analyse the decoders using F-score \cite{16}. Results are shown in Table 3.

| method          | IoU↑ | Chamfer ↓ | NC↑ | F-score↑ |
|-----------------|------|-----------|-----|----------|
| \textit{eigenSDF} | 0.746 | 0.0425 | 0.869 | 0.484 |
| \textit{eigenSDF} (ft) | 0.758 | 0.0325 | 0.896 | 0.529 |
| Linear (\(\phi\)) (chamfer) | 0.582 | 0.050 | 0.773 | 0.315 |
| Linear(voxels) | 0.637 | 0.067 | 0.737 | 0.384 |
| DLS ([24])        | 0.681 | 0.047 | 0.858 | 0.103 |
| TL ([24])         | 0.656 | 0.082 | 0.847 | 0.081 |

Table 3: We compare \textit{eigenSDF} to the state-of-the-art methods in terms of reconstruction. We find that \textit{eigenSDF} performs better than linear autoencoders trained on voxels or SDFs.

4.4 Comparison with Deep Level Sets

In this section, we compare our method to the other recent approach relying on the signed distance transform \cite{22} and learning with the chamfer loss \(L_\varepsilon\). This one, however, uses the CNN decoder model and does not learn a latent shape representation. We have chosen a similar experimental setup of 3 subsets each having 2 000 examples from ShapeNet repository: \textit{cars, sofas, chairs}. We observed that remaining 2 categories, \textit{bottles} and \textit{phones}, are too simple to allow for a difference in higher resolution.

We compare the training time for both methods for various resolutions. The results shown in Figure 2 demonstrates that it is not feasible to use the CNN decoder in higher resolutions. It is consistent with the findings of \cite{25}. Reported metrics, which are shown in Table 4, might differ slightly from \cite{25} due to different pre-processing techniques.
4.5 Reconstruction and Generation

Finally, we evaluate the performance on the single view reconstruction qualitatively. In Figure 4, we can see that reconstructions (on unseen data) can be effective capturing more complex structures ignored by [22]. Multiple authors have also consider generating unconditionally shapes, typically using sophisticated non-linear deep learning models like GANs and VAEs. We compare some of these to sampling a gaussian in the latent space of the eigenSDF. Qualitative results are shown in Figure 3. As it can be seen, our simple approach yields comparable shape representation to the complex non-linear models.

Figure 3: We compare unconditional generations of cars category. Generations from a gaussian fit to eigenSDF is shown in the top row (blue). Second row are generations from [21] and the third row is from a 3D GAN [33].

5 Conclusion

We have shown that using a simple linear decoder coupled with the SDF representation yields competitive results. The SDF lends itself effectively to the application of PCA yielding a strong but simple baseline for future work in learned 3D shape analysis. Moreover, our work suggests that more complex baseline datasets may be needed to further evaluate deep learning methods on 3D shape inference.

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Figure 4: We compare reconstruction of eigenSDF and the CNN decoder based Deep Level Sets [22], which also uses SDF representation. eigenSDF allows us to operate at a higher resolution and generally produces more locally coherent results.

Table 4: Comparison to the SDF based method [22] in single view reconstruction. There is marked improvement due to the ability to model higher resolution.
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