Neural Cages for Detail-Preserving 3D Deformations

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Abstract

We propose a novel learnable representation for detail-preserving shape deformation. The goal of our method is to warp a source shape to match the general structure of a target shape, while preserving the surface details of the source. Our method extends a traditional cage-based deformation technique, where the source shape is enclosed by a coarse control mesh termed cage, and translations prescribed on the cage vertices are interpolated to any point on the source mesh via special weight functions. The use of this sparse cage scaffolding enables preserving surface details regardless of the shape’s intricacy and topology. Our key contribution is a novel neural network architecture for predicting deformations by controlling the cage. We incorporate a differentiable cage-based deformation module in our architecture, and train our network end-to-end. Our method can be trained with common collections of 3D models in an unsupervised fashion, without any cage-specific annotations. We demonstrate the utility of our method for synthesizing shape variations and deformation transfer.

1. Introduction

Deformation of 3D shapes is a ubiquitous task, arising in many vision and graphics applications. For instance, deformation transfer [25] aims to infer a deformation from a given pair of shapes and apply the same deformation to a novel target shape. As another example, a small dataset of shapes from a given category (e.g., chairs) can be augmented by synthesizing variations, where each variation deforms a randomly chosen shape to the proportions and morphology of another while preserving local detail [29, 32].

Deformation techniques usually need to simultaneously optimize at least two competing objectives. The first is alignment with the target, e.g., matching limb positions while deforming a human shape to another human in a different pose. The second objective is adhering to quality metrics, such as distortion minimization and preservation of local geometric features, such as the human’s face. These two objectives are contradictory, since a perfect alignment of a deformed source shape to the target precludes preserving the original details of the source.

Due to these conflicting objectives, optimization techniques [17] require parameter tuning to balance the two competing terms, and are heavily reliant on an inferred or manually supplied correspondence between the source and the target. These parameters vary based on the shape category, representation, and the level of dissimilarity between the source and the target.

To address these limitations, recent techniques train a neural network to predict shape deformations. This is achieved by predicting new positions for all vertices of a template shape [26] or by implicitly representing the deformation as a mapping of all points in 3D, which is then used to map each vertex of a source shape [6, 29]. Examples of the results of some of these methods can be seen in Fig 4, which demonstrates the limitations of such approaches: the predicted deformations corrupt features and exhibit distortion, especially in areas with thin structures, fine details or...
gloss discrepancies between source and target. These artifacts are due to the inherent limitations of neural networks to capture, preserve, and generate high frequencies.

In this paper, we circumvent the above issues via a classic geometry processing technique called cage-based deformation \[14\,15\,18\], abbreviated to CBD. In CBD, the source shape is enclosed in a very coarse scaffold mesh called the cage (Fig 2). The deformation of the cage is transferred to the enclosed shape by interpolating the translations of the cage vertices. Fittingly, the interpolation schemes in these classic works are carefully designed to preserve details and minimize distortion.

Our main technical contribution is a novel neural architecture in which, given a source mesh, learnable parameters are optimized to predict both the positioning of the cage around the source shape, as well as the deformation of that cage, which drives the deformation of the enclosed shape in order to match a target shape. The source shape is deformed by deterministically interpolating the new positions of its surface points from those of the cage vertices, via a novel, differentiable, cage-based deformation layer. The pipeline is trained end-to-end on a collection of randomly chosen pairs of shapes from a training set.

The first key advantage of our method is that cages provide a much more natural space for predicting deformations: CBD is feature-preserving by construction, the degrees of freedom in deformation only depends on the number of vertices on the coarse cage. In short, our network makes a prediction in a low-dimensional space of highly regular deformations.

The second key advantage is that our method is not tied to a single source shape, nor to a single mesh topology. As the many examples in this paper demonstrate, the trained network can predict and deform cages for similar shapes not observed during training. The target shape can be crude and noisy, e.g., a shape acquired with cheap scanning hardware or reconstructed from an image. Furthermore, dense correspondences between the source and target shapes are not required in general, though they can help when the training set has very varied articulations. Thus the method can be trained on large datasets that are not co-registered and do not have consistently labeled landmarks.

We show the utility of our method in two main applications. We generate shape variations by deforming a 3D model using other shapes as well as images as targets. We also use our method to pose a human according to a target humanoid character, and, given a few sparse correspondences, perform deformation transfer and pose an arbitrary novel humanoid. See Figures 1, 7, 9 and 4 for examples.

2. Related work

We now review prior work on learning deformations, traditional methods for shape deformation, and applications.

Learning 3D deformations. Many recent works in learning 3D geometry have focused on generative tasks, such as synthesis [8, 20] and editing [36] of unstructured geometric data. These tasks are especially challenging if one desires high-fidelity content with intricate details. A common approach to producing intricate shapes is to deform an existing generic [28] or category-specific [7] template. Early approaches represented deformations as a single vector of vertex positions of a template [26], which limited their output to shapes constructable by deforming the specific template, and also made the architecture sensitive to the template tessellation. An alternative is to predict a freeform deformation field over 3D voxels [9, 13, 34], however, this makes the deformation’s resolution dependent on the voxel resolution, and thus has limited capability to adapt to a specific shape categories and source shapes.

Alternatively, some architectures learn to map a single point at a time, conditioned on some global descriptor of the target shape [7]. These architectures can also work for novel sources by conditioning the deformation field on features of both source and target [6, 29]. Unfortunately, due to network capacity limits, these techniques struggle to represent intricate details and tend to blur high-frequency features.

Traditional methods for mesh deformation. Research on detail-preserving deformations in the geometry processing community spans several decades and has contributed various formulations and optimization techniques [24]. These methods usually rely on a sparse set of control points whose transformations are interpolated to all remaining points of the shape; the challenge lies in defining this interpolation in a way that preserves details. This can be achieved by solving an optimization problem to reduce the distortion of the deformation such as [23]. However, defining the output deformation as the solution to an intricate non-convex optimization problem significantly limits the ability of a network to learn this deformation space.

Instead, we use cage-based deformations as our representation, where the source shape is enclosed by a coarse cage mesh, and all surface points are written as linear combinations of the cage vertices, i.e., generalized barycentric coordinates. Many designs have been proposed for these coordinate functions such that shape structure and details are preserved under interpolations [2, 14, 15, 18, 21, 27, 31].

Shape synthesis and deformation transfer. Automatically aligning a source shape to a target shape while preserving details is a common task, used to synthesize variations of shapes for amplification of stock datasets [11] or for transferring a given deformation to a new model, targeting animation synthesis [25]. To infer the deformation, correspondence between the two shapes needs to be accounted for, either by explicitly inferring corresponding points [12, 16, 17], or by implicitly conditioning the deformation fields on the latent code of the target shape [6, 9, 29]. Our work builds
3.1. Cage-based deformations

CBD are a type of freeform space deformations. Instead of defining a deformation solely on the surface \( S \), space deformations warp the entire ambient space in which the shape \( S \) is embedded. In particular, a CBD controls this warping via a coarse triangle mesh, called a cage \( C \), which typically encloses \( S \). Given the cage, any point in ambient space \( p \in \mathbb{R}^3 \) is encoded via generalized barycentric coordinates, as a weighted average of the cage vertices \( v_j \):

\[
p = \sum_{0 \leq j < |V_C|} \phi^C_j(p) v_j,
\]

where the weight functions \( \{\phi^C_j\} \) depend on the relative position of \( p \) w.r.t. the cage vertices \( \{v_j\} \). The deformation of any point in ambient space is obtained by simply offsetting the cage vertices and interpolating their new positions \( v'_j \) with the pre-computed weights, i.e.

Previous works on CBD constructed various formulae to attain weight functions \( \{\phi^C_j\} \) with specific properties, such as interpolation, linear precision, smoothness and distortion minimization. We choose mean value coordinates (MVC) [15] for their feature preservation and interpolation properties, as well as simplicity and differentiability w.r.t. the source and deformed cages’ coordinates.

3.2. Learning cage-based deformation

As our goal is an end-to-end pipeline for deforming shapes, we train the network to predict both the source cage and the target cage, in order to optimize the quality of the resulting deformation. Given a source shape \( S_s \) and a target shape \( S_t \), we design a deep neural network that predicts a cage deformation that warps \( S_s \) to \( S_t \) while preserving the details of \( S_s \). Our network is composed of two branches, as illustrated in Fig[2]: a cage-prediction model \( N_C \), which predicts the initial cage \( C_s \) around \( S_s \), and a deformation-prediction model \( N_d \), which predicts an offset from \( C_s \), yielding the deformed cage \( C_{s \rightarrow t} \), i.e.

\[
C_s = N_C(S_s) + C_0, \quad C_{s \rightarrow t} = N_d(S_t, S_s) + C_s
\]

Since both branches are differentiable, they can be both learned jointly in an end-to-end manner.

The branches \( N_C \) and \( N_d \) only predict the cage and do not directly rely on the detailed geometric features of the input shapes. Hence, our network does not require high-resolution input nor involved tuning for the network architectures. In fact, both \( N_C \) and \( N_d \) follow a very streamlined design: their encoders and decoders are simplified versions of the ones used in AtlasNet [8]. We remove the batch normalization and reduce the channel sizes, and instead of feeding 2D surface patches to the decoders, we feed a template cage \( C_0 \) and the predicted initial cage \( C_s \) to the the cage predictor and deformer respectively, and let them predict the offsets. By default, \( C_0 \) is a 42-vertex sphere.

3.3. Loss terms

Our loss incorporates three main terms. The first term optimizes the source cage to encourage positive mean value coordinates. The two latter terms optimize the deformation, the first by measuring alignment to target and the second by measuring shape preservation. Together, these terms comprise our basic loss function:

\[
L = \alpha_{MVC} L_{MVC} + L_{align} + \alpha_{shape} L_{shape}.
\]

We use \( \alpha_{MVC} = 1 \), \( \alpha_{shape} = 0.1 \) in all experiments.

To optimize the mean value coordinates of the source cage, we penalize negative weight values, which emerge when the source cage is highly concave, self-overlapping, or when some of the shape’s points lie outside the cage:
where $\alpha$ is the loss weight, and $\phi_{ji}$ denotes the coordinates of $p_i \in S_s$ w.r.t. $v_j \in C_s$.

$L_{\text{symm}}$ is measured as the chamfer distance between the shape and its reflection around the $x = 0$ plane. We apply this loss to the deformed shape $S_{x\rightarrow t}$ as well as the cage $C_s$. Thus, our final shape preservation loss is: $L_{\text{shape}} = L_{\text{p2f}} + L_{\text{normal}} + L_{\text{symm}}$ for man-made shapes and $L_{\text{shape}} = L_{\text{p2f}}$ for characters.

4. Applications

We now showcase two applications of the trained cage-based deformation network.

4.1. Stock amplification via deformation

Creating high-quality 3D assets requires significant time, technical expertise, and artistic talent. Once the asset is created, the artist commonly deforms the model to create several variations of it. Inspired by prior techniques on automatic stock amplification [29], we use our method to learn a meaningful deformation space over a collection of shapes within the same category, and then use random pairs of source and target shapes to synthesize plausible variations of artist-generated assets.

Training details. We train our model on the chair, car and table categories from ShapeNet [3] using the same splitting into training and testing sets as in Grouix et al. [6]. We then randomly sample 100 pairs from the test set. Each shape is normalized to fit in a unit bounding box and is represented by 1024 points.

Variation synthesis examples. Fig[3] shows variations generated from various source-target pairs, exhibiting the regularization power of the cages: even though our training omits all semantic supervision such as part labels, these variations are plausible and do not exhibit feature distortions; fine details, such as chair slats, are preserved.

Comparisons. We compared our target-driven deformation method to other methods that strive to achieve the same goal. Results are shown in Fig[4]. While in many cases alternative techniques do align the deformed shape the target, in all cases they introduce significant artifacts in the deformed meshes.

We first compare to a non-learning-based approach: non-rigid ICP [10], a classic registration technique that alternates between correspondence estimation and optimization of a non-rigid deformation to best align corresponding points. We show results with the optimal registration parameters we found to achieve detail preservation. Clearly,
Figure 4: Comparison of our method with other non-homogeneous deformation methods. Our method achieves superior detail preservation of the source shape in comparison to optimization-based [10] and learning-based [6, 9, 29] techniques, while still aligning the output to the target.

Figure 5: Quantitative evaluation of our method vs alternative methods. Each point represents a method, embedded according to its average alignment error (Chamfer Distance) and distortion ($\Delta$CotLaplacian). Points near the bottom-left corners are better.

ICP is sensitive to wrong correspondences that cause convergence to artifact-ridden local minima. We also compare to learning-based methods that directly predict per-point transformations and leverage cycle-consistency (CC) [6] or feature-preserving regularization (3DN) [29] to learn low-distortion shape deformations. Both methods blur and omit features, while also creating artifacts by stretching small parts. We also compare to ALIGNet [9], a method that predicts a freeform deformation over a voxel grid, yielding a volumetric deformation of the ambient space similarly to our technique. Contrary to our method, the coarse voxel grid cannot capture the fine deformation of the surface needed to avoid large artifacts. Our training setup is identical to CC, and we retrained 3DN and ALIGNet with the same setup using parameters suggested by the authors.

In Fig 6 we compare our results to the simplest of deformation methods – anisotropic scaling, achieved by simply rescaling the source bounding box to match that of the target. While local structure is well preserved, this method cannot account for the different proportion changes required for different regions, highlighting the necessary intricacy of the optimal deformation in this case.

Quantitative comparisons. In Fig 5 we quantitatively evaluate the various methods using two metrics: distance to the target shape, and detail preservation, measured via
chamfer distance (computed over a dense set of 5000 uniformly sampled points) and difference in cotangent Laplacian, respectively. Note that these metrics do not favor any method, since all optimize for a variant of chamfer distance, and none of the methods optimize for the difference in the cotangent Laplacian. Each 2D point in the figure represents one method, with the point’s coordinates prescribed with respect to the two metrics, the origin being ideal. This figure confirms our qualitative observations: our method is more effective at shape preservation than most alternatives while still capturing the gross structure of the target.

Using images as targets. Often, a 3D target is not readily available. Images are more abundant and much easier to acquire, and thus pose an appealing alternative. We use a learning-based single-view reconstruction technique to generate a proxy target to use with our method to find appropriate deformation parameters. We use publicly available product images of real objects and execute AtlasNet’s SVR reconstruction [8] to generate a coarse 3D proxy as a target. Fig 7 shows that even though the proxy has coarse geometry and many artifacts, these issues do not affect the deformation, and the result is still a valid variation of the source.

4.2. Deformation transfer

Given a novel 3D model, it is much more time-efficient to automatically deform it to mimic an existing example deformation, than having an artist deform the novel model directly. This automatic task is called deformation transfer. The example deformation is given via a model in a rest pose $S_s$, and a model in the deformed pose $S_t$. The novel 3D model is given in a corresponding rest pose $S_s'$. The goal is to deform the novel model to a position $S_t'$ so that the deformation $S_s' \rightarrow S_t'$ is analogous to $S_s \rightarrow S_t$. This task can be quite challenging, as the example deformation $S_t$ may have very different geometry, or even come from an ad-hoc scan, and thus dense correspondences between $S_s$ and $S_t$ are unavailable, preventing the use of traditional mesh optimization techniques such as [25]. Furthermore, as the novel character $S_s'$ may be significantly different from all models observed during training, it is impossible to a-priori learn a deformation subspace for $S_s'$ unless sufficient pose variations of $S_s'$ is available, as in Gao et al. [4].

We demonstrate that our learning-based approach can be used to perform deformation transfer on arbitrary humanoid models. The network infers the deformation from the source $S_s$ to the target $S_t$, without any given correspondences, and then an optimization-based method transfers this deformation to a novel shape $S_s'$, to obtain the desired deformation $S_t'$. Hence, given any arbitrarily-complex novel character, all our method requires are sparse correspondences supplying the necessary alignment between the two rest poses, $S_s$ and $S_t$. We now overview the details of our learned cage-based human deformation model and the optimization technique used to transfer the deformations.

Learning cage-based human deformation. To train our human-specific deformation model, we use the dataset [7] generated using the SMPL model [1] of 230K models of various humans in various poses. Since our application assumes that the exemplar deformation is produced from a single canonical character, we picked one human in the dataset to serve as $S_s$. Subsequently, since we only have one static source shape $S_s$, we use a static cage $C_s$ manually created with 77 vertices, and hence do not need the cage prediction network $N_c$ and only use the deformation network $N_d$. We train $N_d$ to deform the static $S_s$ using the static $C_s$ into exemplars $S_t$ from the dataset (with targets not necessarily stemming from the same humanoid model as $S_s$). We then train with the loss in [3], but with one modification: in similar fashion to prior work, during training we use ground truth correspondences and hence replace the chamfer distance with the L2 distance w.r.t the known correspondences. Note that these correspondences are not used at inference time.

Lastly, during training we also optimize the static source cage $C_s$ by treating its vertices as degrees of freedom and directly optimizing them to reduce the loss so as to attain a more optimal, but still static cage after training.

Fig 8 shows examples of human-specific cage deformations predicted for test targets (not observed while training). Note how our model successfully matches poses even without knowing correspondences at inference time, while preserving fine geometric details such as faces and fingers.
Transferring cage deformations. After training, we have at our disposal the deformation network \( \mathcal{N}_d \) and the static \( C_s, S_s \). We assume to be given a novel character \( S_{n} \) with 83 landmark correspondences aligning it to \( S_s \), and an example target pose \( S_t \). Our goal is to deform \( S_{n} \) into a new pose \( S_{n'} \) that is analogous to the deformation of \( S_s \) into \( S_t \).

We first generate a new cage \( C_{n'} \) for the character \( S_{n'} \). Instead of a network-based prediction, we simply optimize the static cage \( C_s \), trying to match mean value coordinates between corresponding points of \( S_s, S_{n'} \):

\[
\mathcal{L}_{\text{consistency}} = \sum_{j} \sum_{(p,q)} \| \phi_{j}^{C_s}(p) - \phi_{j}^{C_{n'}}(q) \|^2
\]

(7)

where \((p,q)\) are corresponding landmarks. We also regularize with respect to the cotangent Laplacian of the cage:

\[
\mathcal{L}_{\text{lap}} = \sum_{0 \leq j < |C_s|} \left( ||L_{\text{cot}} v_j || - ||L_{\text{cot}} v_j' || \right)^2.
\]

(8)

Then, we compute \( C_{n'} \) by minimizing \( \mathcal{L} = \mathcal{L}_{\text{consistency}} + 0.05 \mathcal{L}_{\text{lap}} \), with \( C_s \) used as initialization, solved via the Adam optimizer with step size \( 5 \cdot 10^{-4} \) and up to \( 10^4 \) iterations (or until \( \mathcal{L}_{\text{consistency}} < 10^{-5} \)).

Finally, given the cage \( C_{n'} \) for the novel character, we compute the deformed cage \( C_{n' \rightarrow n''} \), using our trained deformation network, by applying the predicted offset to the optimized cage: \( C_{n' \rightarrow n''} = \mathcal{N}_d (S_t, S_{n'}) + C_{n'} \). The final deformed shape \( S_{n''} \) is computed by deforming \( S_{n'} \) using the cage \( C_{n' \rightarrow n''} \) via (1). This procedure is illustrated in Fig 10 while more examples can be found in the supplemental material. Due to the agnostic nature of cage-deformations to the underlying shape, we are able to seamlessly combine machine learning and traditional geometry processing to generalize to never-observed characters. To demonstrate the expressiveness of our method, we show examples on extremely dissimilar target characters in Figures 1 and 9.

5. Evaluation

In this section, we study the effects and necessity of the most relevant components of our methods. To measure the matching error we use chamfer distance computed on 5000 uniformly resampled points, and to measure the feature distortion we use the distance between cotangent Laplacians. All models are normalized to a unit bounding box.

Benefit of learning CBD from data. Instead of learning the CBD from a collection of data, one could minimize (3) for a single pair of shapes, which is essentially a non-rigid Iterative-Closest-Point (ICP) parameterised by cage vertices. As shown in Fig 11 when correct correspondence estimation becomes challenging, the optimization alternative produces non-plausible outputs. In contrast, the learnt approach utilizes domain knowledge embedded in the network’s parameters [22, 35], amounting to better reasoning about the plausibility of inter-shape correspondences and deformations. The learned domain knowledge can generalize to new data. As demonstrated in Sec 4.2 even though our network is trained with ground-truth correspondences, it is able to automatically associate the source shape to a new target without correspondences during inference, while optimization methods require accurate correspondence estimation for every new target.

Effect of the negative MVC penalty, \( \mathcal{L}_{\text{MVC}} \). In Fig 12 we show the effect of penalizing negative mean value coordinates. We train our architecture on 300 vase shapes from COSEG [30], while varying the weight \( \alpha_{\text{MVC}} \in \{0,1,10\} \). Increasing this term brings the cages closer to the shapes’ convex hulls, leading to more conservative deformations. Quantitative results in Table 1 also suggest that increasing the weight \( \alpha_{\text{MVC}} \) favors shape preservation over alignment accuracy. Completely eliminating this term hurts convergence, and increases the alignment error further.
6. Conclusion

We show that classical cage-based deformation provides a low-dimensional, detail-preserving deformation space directly usable in a deep-learning setting. We implement cage weight computation and cage-based deformation as differentiable network layers, which could be used in other architectures. Our method succeeds in generating feature-preserving deformations for synthesizing shape variations and deformation transfer, and better preserves salient geometric features than competing methods.

A limitation of our approach is that we focus on the deformation quality produced by the predicted cages: hence, the cage geometry itself is not designed to be comparable to professionally-created cages for 3D artists. Second, our losses are not quite sufficient to always ensure rectilinear/planar/parallel structures in man-made shapes are perfectly preserved (Fig [13]). Third, for certain types of deformations other parameterizations might be a more natural choice, such as skeleton-based deformation for articulations, nonetheless the idea presented in this paper can be adopted for similarly.

Our method provides an extensible and versatile framework for data-driven generation of high detail 3D geometry. In the future we would like to incorporate alternative cage weight computation layers, such as Green Coordinates [13]. Unlike MVC, this technique is not affine-invariant, and thus would introduce less affine distortion for large articulations (see the second row fourth column in Fig [2]). We also plan to use our method in other applications such as registration, part assembly, and generating animations.

Acknowledgments

We thank Rana Hanocka and Dominic Jack for their extensive help. The robot model in Figures [1] and [9] is from SketchFab, licensed under CC-BY. This work was supported in part by gifts from Adobe, Facebook and Snap.
References


