Neural Algorithms for Precise Shape Completion

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Abstract

The availability of affordable and portable depth sensors has made scanning people and objects simpler than ever. Data acquisition using such sensors is often done from a single view point, and results in an incomplete point cloud. Many downstream tasks require the completion of the partial observation to recover the full shape, with the required fidelity of completion being task dependent.

In this work, we focus on completions of non-rigid objects with especially high fidelity. Applications such as telepresence communication or medical imaging often require that the completion is precise, with no hallucination of shape details taking place. Clearly, such a requirement is only viable given access to additional measurements or prior information. Here, we focus on the latter case, in a setting we coin precise shape completion. More specifically, given the geometry of a full, articulated object in a given pose, as well as a partial scan of the same object in a different pose, we address the new problem of matching the part to the whole while simultaneously reconstructing the new pose from its partial observation.

Our approach is data-driven and takes the form of a Siamese autoencoder without the requirement of a consistent vertex labeling at inference time; as such, it can be used on unorganized point clouds as well as on triangle meshes. We demonstrate the practical effectiveness of our model in the applications of single-view deformable shape completion and dense shape correspondence, both on synthetic and real-world geometric data, where we outperform prior work by a large margin.
Chapter 1

Introduction

One of Aristotle's renowned sayings declares “the whole is greater than the sum of its parts”. This fundamental observation was narrowed down to human perception of planar shapes by the Gestalt psychology school of thought in the twentieth century. A guiding idea of Gestalt theory is the principle of reification, arguing that human perception contains more spatial information than can be extracted from the sensory stimulus, and thus giving rise to the view that the mind generates the additional information based on verbatim acquired patterns. Here, we adopt this line of thought in the context of non-rigid shape completion. Specifically, we argue that given access to a complete shape in one pose, one can accurately complete partial views of that shape at any other pose.

3D data acquisition using depth sensors is often done from a single viewpoint, resulting in an incomplete point cloud. Many downstream applications require completing the partial observations and recovering the full shape. Based on this need, the task of shape completion has been extensively studied in the literature. The required fidelity of completion, however, is task dependent. In fact, in many cases even an approximate completion would be satisfying. For example, completing a car captured from one side by assuming the occluded side is symmetric would be perfectly acceptable for the purpose of obstacle avoidance in autonomous navigation, even if in reality the other side of that car has a large dent. In other cases, however, e.g. when capturing a person for telepresence or medical procedure purposes, it is crucial that the completion is exact, and no hallucina-
tion of shape details takes place. Clearly, this requirement is only viable given access to additional measurements or prior information. Here, we wish to focus on the latter case, which we coin as *precise shape completion*. In particular, provided a complete *non-rigid* shape in one pose, we require a solution for completing a partial view of the same shape in a different pose that is *accurate*, *fast*, and can handle *single-view partiality* resulting from self-occlusion. In this work we make a first attempt to address this specific setting, as opposed to the ubiquitous regime of precise *pose*-reconstruction, and as such, we focus solely on types of partialities that induce mild pose ambiguity.

Existing methods for rigid and non-rigid shape completion from partial scans fall largely into two categories: generative and alignment based. Generative methods have proven to be very powerful in completing shapes by learning to match the class distribution. However, they inherently aim at solving an ill-posed problem. Namely, they assume access only to the partial observation at inference time, and thus are incapable of performing *precise* shape completion of shapes unseen at train time. Non-rigid registration methods can take a full shape and align it to a partial observation and thus fit our prescribed setting. However, state of art methods are slow, and can usually handle only mild partiality. Here we propose a new method for precise completion of a partial non-rigid shape in an arbitrary (target) pose, given the full shape in a different (source) pose. Our method is fast, accurate and can handle severe partiality. Based on a deep neural network for point clouds, we learn a function that encodes the partial and full shapes, and outputs the complete shape at the target pose. By providing the full shape, our completion achieves much higher accuracy than existing methods. Since completion in done a single feed-forward pass our solution is orders of magnitude faster than competing methods. In addition, our generated training set of rendered partial views and their corresponding complete shapes covers a broad range of plausible human poses, appearances and partialities which allows our method to gracefully generalize to unseen instances. Finally, our solution effortlessly recovers dense correspondences between the partial and full shapes that considerably improves state of the art performance on the FAUST projection benchmark.
Our main contributions can be summarized as follows:

1. We introduce a deep Siamese architecture to tackle precise non-rigid shape completion;

2. Our solution is significantly faster, more accurate and can handle more severe partialities than previous methods.

3. The recovered correspondences achieve state-of-the-art performance in partial shape correspondence.

Related work

Roughly speaking, there exist three approaches that address the challenge of reconstructing the geometry of an articulated shape from its partial scan, namely, partial non-rigid registration of surfaces, surface registration to a known skeleton, and shape completion of a given partial surface. While the first approach is the closest to our setting, none of these approaches has yet provided a good solution to the described application. Currently, state-of-the-art partial nonrigid shape registration/alignment [MWZ+18, MMRC18, GFK+18a] methods do not handle the significant partiality one often obtains when using commodity depth sensors, and their processing time even for a moderate-size point clouds of few thousand vertices vary between few minutes at best, to a few hours. In our experimental section, we compare with the most efficient methods belonging to this class.

The methods that can handle substantial partiality usually rely on some modification of the iterative closest point (ICP) algorithm and often have difficulties in handling large deformations between the full and the partial shape [SBCI17, NFS15]. Another existing approach for the non-rigid alignment problem is to use an explicit deformation model such as skeleton rigging. These methods often completely ignore the detailed geometric and textural information in the actual scanned surface. Moreover, they rely on a rigged model for the full template, which is a limiting assumption when the full model is not restricted to a standard pose. The shape completion setting, as explained below, does not accommodate the full shape and therefore hallucinates details by construction, resulting
in inferior completions, as shown by our results and ablation sections. We now turn to review some of the above approaches in more detail.

**Shape Completion**

Recovering a complete shape from partial or noisy measurements is a longstanding research problem that comes in many flavors. In an early attempt to use one pose in order to geometrically reconstruct another, Devir et al. [DRB+09] considered mapping a model shape in a given pose onto a noisy version of the shape in a different pose. Elad and Kimmel were the first to treat shapes as metric spaces [EK01, EK03]. They matched shapes by comparing second order moments of embedding the intrinsic metric into a Euclidean one via classical scaling. In the context of deformable shapes, early efforts focused on completion based on geometric priors [KH13] or reoccurring patterns [BBK06c, KOA15, SVS17, LRB16]. These methods are not suited for severe partiality. For such cases model-based techniques are quite popular, for example, category-specific parametric morphable models that can be fitted to the partial data [BV99, GMFB+17, LMR+15, ACPH06, SSK18]. Model-based shape completion was demonstrated for keypoints input [ASK+05], and was recently proven to be quite useful for recovering 3D body shapes from 2D images [VRM+17, VCR+18, GK19, ZMS18]. Parametric morphable models [BV99], coupled with axiomatic image formation models were used to train a network to reconstruct face geometry from images [RSK16, RSOEK17, SRK17]. Still, much less attention has been given to the task of fitting a model to a partial 3D point cloud. Recently, Jiang et al. [JCZ19] tackled this problem using a skeleton-aware architecture. However, their approach works well when full coverage of the underlying shape is given. [SLK19] proposed a real time solution based on a reinforcement learning agent controlled by a GAN network. [HHSZ19] reconstructed a 3D completion by generating and back-projecting multi-view depth maps. [WZZ+18] focused on the ambiguity in completion from a single view, and suggested to address it using adversarially learned shape priors. Finally, [SG18] suggested a weakly supervised approach and showed performance on realistic data.

**Nonrigid Partial Shape Matching**

Dense non-rigid shape correspondence [KLF11, CK15, LRR+17, HLR+19, RRBW+14,
BBK06b, CPR+19] is a key challenge in 3D computer vision and graphics, and has been widely explored in the last few years. A particularly challenging setting arises whenever one of the two shapes has missing geometry. Bronstein et al.[BBK03, BBK05, BBK06c, BBBK06, BBK06a, BBK07] dealt with partial matching of articulated objects in various scenarios, including pruning of the intrinsic structure while accounting for cuts. This setting has been tackled with moderate success in a few recent papers [RCB+15, LRBB17, RTO+19], however, it largely remains an open problem whenever the partial shape exhibits severe artifacts or large, irregular missing parts. In this paper we tackle precisely this setting, demonstrating unprecedented performance on a variety of real-world and synthetic datasets.

Deep Learning of Surfaces

Following the success of convolutional neural networks on images in the recent years, the geometry processing community has been rapidly adopting and designing computational modules suited for such data. The main challenge is that unlike images, geometric structures like surfaces come in many types of representations, and each requires a unique handling. Early efforts focused on a simple extension from a single image to multi-view representations [SMKLM15, WHC+16]. Another natural extension are 3D CNNs on volumetric grids [WSK+15]. A host of techniques for mesh processing were developed as part of a research branch termed geometric deep learning [BBL+17]. These include graph-based methods [VBV17, WSL+19, HHF+19], intrinsic patch extraction [MBBV15, BMRB16, MBM+17], and spectral techniques [LRR+17, HLR+19]. Point cloud networks [QSMG17, QYSG17] have recently gained much attention. Offering a light-weight computation restricted to sparse points with a sound geometric explanation [JRZK19], these networks have shown to provide a good compromise between complexity and accuracy, and are dominating the field of 3D object detection [QLHG19, XAJ18], semantic segmentation [GEvdM18, BSLF17], and even temporal point cloud processing [CGS19, LYB19]. For generative methods, recent implicit and parametric methods have demonstrated promising results [GFK+18b, PFS+19]. Following the success of encoding non-rigid shape deformations using a point cloud network [GFK+18a], here, we
also choose to use a point cloud representation. Importantly, while the approach presented in [GFK+18a] predicts alignment of two shapes, it is not designed to handle severe partiality, and assumes a fixed template for the source shape. Instead, we show how to align arbitrary input shapes and focus on such a partiality.
Chapter 2

Learning to Complete Shapes

2.1 Method

2.1.1 Overview

We represent shapes as point clouds $S = \{s_i\}_{i=1}^{n_s}$ embedded in $\mathbb{R}^3$. Depending on the setting, each point may carry additional semantic or geometric information encoded as feature vectors in $\mathbb{R}^d$. For simplicity we will keep $d = 3$ in our formulation. Given a full shape $Q = \{q_i\}_{i=1}^{n_q}$ and its partial view in a different pose $P = \{p_i\}_{i=1}^{n_p}$, our goal is to find a nonlinear function $F : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ aligning $Q$ to $P$. If $R = \{r_i\}_{i=1}^{n_r}$ is the (unknown) full shape such that $P \subset R$, ideally we would like to ensure that $F(Q) = R$, where equality should be understood as same underlying surface. Thus, the deformed shape $F(Q)$ acts as a proxy to solve for the correspondence between the part $P$ and the whole $Q$. By calculating for every vertex in $P$ its nearest neighbor in $R \approx F(Q)$, we trivially obtain the mapping from $P$ to $Q$. The deformation function $F$ depends on the input pair of shapes $(P, Q)$. We model this dependency by considering a parametric function $F_\theta : \mathbb{R}^3 \rightarrow \mathbb{R}^3$, where $\theta$ is a latent encoding of the input pair $(P, Q)$. We implement this idea via an encoder-decoder neural network, and learn the space of parametric deformations from example pairs of partial and complete shapes, together with full uncropped versions of the partial shapes.

\footnote{In our setting, we assume that the pose can be inferred from the partial shape \textit{(e.g., an entirely missing limb would make the prediction ambiguous)}, hence the deformation function $F$ is well defined.}
Figure 2.1: **Network Architecture.** Siamese encoder architecture at the top, and the decoder (generator) architecture at the bottom. A shape is provided to the encoder as a list of 6D points, representing the spatial and unit normal coordinates. The latent codes of the input shapes $\theta_{\text{part}}(P)$ and $\theta_{\text{whole}}(Q)$ are concatenated to form a latent code $\theta$ representing the input pair. Based on this latent code, the decoder deforms the full shape by operating on each of its points with the same function. The result is the deformed full shape $F_\theta(Q)$.

serving as the ground truth completion. Our network is composed of an encoder $E$ and a generator $F_\theta$. The encoder takes as input the pair $(P, Q)$ and embeds it into a latent code $\theta$. To map points from $Q$ to their new location, we feed them to the generator along with the latent code. Our network architecture shares a common factor with 3D-CODED architecture [GFK+18a], namely the deformation of one shape based on the latent code of the another. However [GFK+18a] uses a fixed template and is therefore only suited for no or mild partiality, as the template cannot make up for lost shape details in the part. Our pipeline on the other hand, is designed to merge two sources of information into the reconstructed model, resulting in an accurate reconstruction under extreme partiality. In
the supplementary we perform an analysis where we train our network in a fixed-template setting, similar to 3D-CODED and demonstrate the advantage of our paradigm. In what follows we first describe each module, and then give details on the training procedure and the loss function. We refer to Figure 2.1 for a schematic illustration of our learning model.

2.1.2 Encoder

We encode $P$ and $Q$ using a Siamese pair of single-shape encoders, each producing a global shape descriptor (respectively $\theta_{\text{part}}$ and $\theta_{\text{whole}}$). The two codes are then concatenated so as to encode the information of the specific pair of shapes, $\theta = [\theta_{\text{part}}, \theta_{\text{whole}}]$. Considering the specific architecture of the single-shape encoder, we think about the encoder network as a channel transforming geometric information to a vector representation. We would like to utilize architectures which have been empirically proven to encode the 3D surface with the least loss of information, thus enabling the decoder to convert the resulting latent code $\theta$ to an accurate spatial deformation $F_{\theta}$. Encouraged by recent methods [GFK+18b, GFK+18a] that showed detailed reconstruction using PointNet [QSMG17], we also adopt it as our backbone encoder. We provide the encoder 6 input channels, representing the vertex location and the vertex normal field. We justify this design choice in section 2.1.6. Specifically, our encoder passes all 6D points of the input shape through the same 'mlp' units, of hidden dimensions $(64, 128, 1024)$. Here, the term mlp, carries the same meaning as in PointNet, i.e. multi-layer perceptron, with ReLU activation, and batch normalization layers. After a max-pool operation over the input points, we receive a single 1024-dimensional vector. Finally, we apply a linear layer of size 1024 and a ReLu activation function. Hence, each shape in the input pair is represented by a latent code $\theta_{\text{whole}}, \theta_{\text{part}}$ of size 1024 respectively. We concatenate these to a joint representation $\theta$ of size 2048.

2.1.3 Generator

Given the code $\theta$, representing the partial and full shapes, the generator has to predict the deformation function $F_{\theta}$ to be applied to the full shape $Q$. We realize $F_{\theta}$ as a Multi-Layer
Perceptron (MLP) that maps an input point $q_i$ on the full shape $Q$, to its corresponding output point $r_i$ on the ground truth completed shape. The MLP operates pointwise on the tuple $(q_i, \theta)$, with $\theta$ kept fixed. The result is the destination location $F_\theta(q_i) \in \mathbb{R}^3$, for each input point of the full shape $Q$. This generator architecture allows, in principle, to calculate the output reconstruction in a flexible resolution, by providing the generator a full shape with some desired output resolution. In detail, the generator consists of 9 layers of hidden dimensions $(2054, 1024, 512, 256, 128, 128, 128, 128, 128, 3)$, followed by a hyperbolic tangent activation function. The output of the decoder is the 3D coordinates. In addition, we can compute a normal field based on the vertex coordinates, making the overall output of the decoder a 6D point. The normal is calculated using the known connectivity of the full shape $Q$, from our training dataset. Thus, the reconstruction loss in the below section could be generalized and defined using the normal output channel, as well. In the implementation section, we ablate this design choice, and show it leads to a performance improvement.

2.1.4 Loss function

The loss definition should reflect the visual plausibility of the reconstructed shape. Measuring such a quality analytically is a challenging problem worth studying on itself. Yet, in this paper we adopt a naive measurement of the Euclidean proximity between the ground-truth and the reconstruction. Formally, we define the loss as,

$$L(P, Q, R) = \sum_{i=0}^{n_q} \left\| F_{\theta(P,Q)}(q_i) - r_i \right\|^2,$$

(2.1)

where $r_i = \pi^*(q_i) \in R$ is the matched point of $q_i \in Q$, given by the ground-truth mapping $\pi^*: Q \to R$.

2.1.5 Training Procedure

We train our model using samples from datasets of human shapes. These contain 3D models of different subjects in various poses. The datasets are described in detail in
Section 2.2.1. Each training sample is a triplet \((P, Q, R)\) of a partial shape \(P\), a full shape \(Q\) in a different pose \(Q\) and a ground truth completion \(R\). The shapes \(Q\) and \(R\) are sampled from the same subject in two different poses. To receive \(P\) we render a depth map of \(R\), at a viewpoint of zero elevation and a random azimuth angle in the range \(0^\circ\) and \(360^\circ\). These projections approximate the typical partiality pattern of depth sensors. Note that despite the large missing region, these projections largely retain the pose, making the reconstruction task well-defined. We also analysed different types of projections, such as projections from different elevation angles. This analysis is provided in the supplementary.

The training examples \((P_n, Q_n, R_n)_{n=1}^N\) were provided in batches to the Siamese Network, where \(N\) is the size of the train set. Each input pair is fed to the encoder to receive the latent code \(\theta(P_n, Q_n)\) and the reconstruction \(F_{\theta(P_n, Q_n)}(Q_n)\) is determined by the generator. This reconstruction is subsequently compared against the ground-truth reconstruction \(R_n\) using the loss in Eq. (2.1).

### 2.1.6 Implementation Considerations

The network was trained using the PyTorch [PGC+17] ADAM optimizer with a learning rate of 0.001 and a momentum of 0.9. Each training batch contained 10 triplet examples \((P, Q, R)\). The network was trained for 50 epochs, each containing 1000 batches. The input shapes, \(Q\) and \(R\), are were centered, such that their center of mass lies at the origin.

**Surface Normals**

In practice we found it helpful to include normal vectors as additional input features, making each input point 6D. The normal vector field is especially helpful for disambiguating contact points of the surface allowing prevention of contradicting requirements of the estimated deformation function. The input normals were computed using the connectivity for the mesh inputs, and approximated using Hoppe’s method [HDD+92] for point clouds, as described in the experimental section. We note that at training, we always had access to the mesh connectivity and Hoppe’s method was only applied on real scans, at inference time. Additionally, in the loss evaluation, we found that by considering also surface normals, in addition to point coordinates, fine details are better preserved. Therefore, in
equation (2.1), we defined \( r_i \) as the concatenation of the coordinates and unit normal vector at each point: \((\vec{x}_{ri}, \alpha \vec{n}_{ri}) \in \mathbb{R}^6\). We used a scale factor of \( \alpha = 0.1 \), for the normal vector. To conclude, we used the surface normals in two places: (A) as additional channels for the input shapes, and (B) in the loss definition. To quantify the contribution of each design choice we ran all 4 configurations on FAUST dataset [BRLB14]. The relative improvement w.r.t not using normals at all is as follows: A+\B-: 4.6%; A-\B+: −3.3%; A+\B+ (as in the paper): 13%. Our experiments indicate that setting A+ is consistently helpful in disambiguating contact points, and that the chosen setting A+\B+, is the best performing.

**ICP Refinement**

Empirically, the network reconstruction is often slightly shifted from the source partial scan. To recover the partial correspondence via a nearest neighbor query, it is crucial that the alignment be as exact as possible, and therefore we apply a rigid Iterative Closest Point algorithm [BM92], as refinement, choosing the moving input as the partial shape, and the fixed input as the network reconstruction. Since the initial alignment is already adequate, this step is both stable and fast.

**Activation Function**

Studying the displacement field statistics between all pose pairs in our training datasets, we observed that the maximal coordinate displacement is bounded by 1.804m, and relatively symmetric. Accordingly, in the generator module, we used the activation \(2\times \tanh(x)\) - a symmetric function, bounded in the range \([-2,2]\), akin to [GFK+18a].

### 2.2 Experiments

The proposed method tackles two important tasks in nonrigid shape analysis: shape completion and partial shape matching. We emphasize the graceful handling of severe partiality resulting from range scans. In contrast, prior efforts either addressed one of these tasks or attempted to address both at mild partiality conditions. Here, we describe the different datasets used and then evaluate our method on both tasks. Finally, we show
performance on real scanned data.

2.2.1 Datasets

We utilize two datasets of human shapes for training and evaluation, FAUST [BRLB14] and AMASS [MGT+19]. In addition we use raw scans from Dynamic FAUST [BRPMB17] for testing purposes only. FAUST was generated by fitting SMPL parametric body model [LMR+15] to raw scans. It is a relatively small set of 10 subjects posing at 10 poses each. Following training and evaluation protocols from previous works (e.g. [LRR+17]), we kept the same train/test split, and for each of these sets, we generated 10 projected views per model, using pyRender [HZFG19]. AMASS, on the other hand, is currently the largest and most diverse dataset of human shapes designed specifically for deep learning applications. It was generated by unifying 15 archived datasets of marker-based optical motion capture (mocap) data. Each mocap sequence was converted to a sequence of rigged meshes using SMPL+H model [RTB17]. Consequently, AMASS provides a richer resource for evaluating generalization. We generated a large set of single-view projections by sampling every 100th frame of all provided sequences. We then used pyRender [HZFG19] to render each shape from 10 equally spaced azimuth angles, keeping elevation at zero. Keeping the data splits prescribed by [MGT+19], our dataset comprises a total of 110K, 10K, and 1K full shapes for train, validation and test, respectively; and 10 times that in partial shapes. Note that at train time we randomly mix and match full shapes and their parts which drastically increases the effective set size.

2.2.2 Methods In Comparison

The problem of deformable shape completion was recently studied by Litany et al.[LBBM18]. In their work, completion is achieved via optimization in a learned shape space. Different from us, their task is completion from a partial view without explicit access to a full model. This is an important distinction as it means missing parts can only be hallucinated. In contrast, we assume the shape details are provided but are not in the correct pose. Moreover, their solution requires a preliminary step of solving partial matching to a template model,
which by itself is a hard problem. Here, we solve for it jointly with the alignment. The optimization at inference time also makes their solution quite slow. Instead we output a result in a single feed forward fashion. 3D-CODED [GFK+18a] performs template alignment to an input shape in two stages: fast inference and slow refinement. It is designed for inputs which are either full or has mild partiality. Here we evaluate the performance of their network predictions under significant partiality. In the refinement step we use directional Chamfer distance, as suggested by the authors in the partial case. FARM [MMRC18] is another alignment-based solution that has shown impressive results on shape completion and dense correspondences. It builds on the SMPL [LMR+15] human body model due to its compact parameterization, yet, we found it to be very slow to converge (up to 30 min for a single shape) and prone to getting trapped in local minima. We also tried to compare with a recent nonrigid registration method [MWZ+18] that aligns a given full source point cloud to a partial target point cloud. However, this method didn’t converge on our moderate size point clouds (< 7000 vertices) even within 48 hours, therefore we do not report on this method. 3D-EPN [DQN16] is a rigid shape completion method. Based on a 3D-CNN, it accepts a voxelized signed distance field as input, and outputs that of a completed shape. Results are then converted to a mesh via computation of an isosurface. Comparison with classic Poisson reconstruction [KH13] is also provided. It serves as a naïve baseline as it has access only to the partial input. Lacking a single good measure of completion quality, we provide 5 different ones (see tables 2.1 and 2.2). Each measurement highlights a different aspect of the predicted completion. We report the root mean square error (RMSE) of the Euclidean distance between each point on the reconstructed shape and its ground truth mapping. We report this measure for predictions with well defined correspondence to the true reconstruction. We also report the RMSE of two directional Chamfer distances: ground-truth to prediction, and vice versa. The former measures coverage of the target shape by the prediction and the later penalizes prediction outliers. We report the sum of both as full the Chamfer distance. Finally, we report volumetric error as the absolute volume difference divided by the ground truth volume. Please note that the results reported in [LBBM18] as “Euclidean distance error” are reported differently in
our Table 2.1 and 2.2. We confirm that the column named “Euclidean Distance Error” in [LBBM18] is, in fact, a directional Chamfer distance from ground truth to reconstruction. We, therefore, reported that error in the appropriate column and added a computation of the Euclidean distance.

2.2.3 Single View Completion

We evaluate our method on the task of deformable shape completion on FAUST and AMASS.

FAUST Projections

We follow the evaluation protocol proposed in [LBBM18] and summarize the completion results of our method and prior art in Table 2.1. As can be seen, our network generates a much more accurate completion. Contrary to optimization-based methods [LBBM18, GFK+18a, MMRC18] which are very slow at inference, our feed-forward network performs inference in less than a second. To better appreciate the quality of our reconstructions, in Figure 2.3 we visualize completions predicted by various methods. Note how our method accurately preserves fine details that were lost in previous methods. In the supplementary, we analyse the reconstruction error as a function of proximity between the source and the target pose, as well as provide additional completion results.

AMASS Projections

Using our test set of partial shapes from AMASS (generated as described in 2.2.1), we compare our method with two recent methods based on shape alignment: 3D-CODED [GFK+18a], and FARM [MMRC18]. As described in 2.2.2, 3D-CODED is a learning-based method that uses a fixed template and is not designed to handle severe partiality. FARM, on the other hand, is an optimization method built for the same setting as ours. We summarize the results in Table 2.2. As can be seen, our method outperforms the two baselines by a large margin in all reported metrics. Note that on some of the examples (about 30%) FARM crashed during the optimization. We therefore only report the errors on its successful runs. Visualizations of several completions are shown in Figure 2.2. Additional completions are visualized in the supplementary.
Table 2.1: **FAUST Shape Completion.** Comparison of different methods with respect to errors in vertex position and shape volume.

<table>
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<tbody>
<tr>
<td>Poisson [KH13]</td>
<td>–</td>
<td>24.8 ± 23.2</td>
<td>7.3</td>
<td>3.64</td>
<td>10.94</td>
</tr>
<tr>
<td>3D-EPN [DQN16]</td>
<td>–</td>
<td>89.7 ± 33.8</td>
<td>4.52</td>
<td>4.87</td>
<td>9.39</td>
</tr>
<tr>
<td>3D-CODED [GFK+18a]</td>
<td>35.50</td>
<td>21.8 ± 0.3</td>
<td>11.15</td>
<td>38.49</td>
<td>49.64</td>
</tr>
<tr>
<td>FARM [MMRC18]</td>
<td>35.77</td>
<td>43.08 ± 20.4</td>
<td>9.5</td>
<td>3.9</td>
<td>13.4</td>
</tr>
<tr>
<td>Litany <em>et al.</em> [LBBM18]</td>
<td>7.07</td>
<td>9.24 ± 8.62</td>
<td>2.84</td>
<td>2.9</td>
<td>5.74</td>
</tr>
<tr>
<td><strong>Ours</strong></td>
<td><strong>2.94</strong></td>
<td><strong>7.05 ± 3.45</strong></td>
<td><strong>2.42</strong></td>
<td><strong>1.95</strong></td>
<td><strong>4.37</strong></td>
</tr>
</tbody>
</table>

Table 2.2: **AMASS Shape Completion.** Comparison of different methods with respect to errors in vertex position and shape volume.

<table>
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<tbody>
<tr>
<td>3D-CODED [GFK+18a]</td>
<td>36.14</td>
<td>–</td>
<td>13.65</td>
<td>35.35</td>
<td>49</td>
</tr>
<tr>
<td>FARM [MMRC18]</td>
<td>27.75</td>
<td>49.42 ± 29.12</td>
<td>11.17</td>
<td>5.14</td>
<td>16.31</td>
</tr>
<tr>
<td><strong>Ours</strong></td>
<td><strong>6.58</strong></td>
<td><strong>27.62 ± 15.27</strong></td>
<td><strong>4.86</strong></td>
<td><strong>3.06</strong></td>
<td><strong>7.92</strong></td>
</tr>
</tbody>
</table>

2.2.4 **Non-rigid Partial Correspondences**

Finding dense correspondences between a full shape and its deformed parts is still an active research topic. Here we propose a solution in the form of alignment between the full shape and the partial shape, allowing for the recovery of the correspondence by a simple nearest neighbor search. As before, we evaluate this task on both FAUST and AMASS.

**FAUST Projections**

On the FAUST projections dataset, we compare with two alignment-based methods, FARM and 3D-CODED. We also compare with 3 methods designed to only recover correspondences, that is, without performing shape completion: MoNet [MBM+17], and two 3-layered Euclidean CNN baselines, trained on either SHOT [TSDS10] descriptors or depth maps. Results are reported in Figure 2.4. As in the single view completion experiment, the test set consists of 200 shapes: 2 subjects at 10 different poses with 10 projected views each. The direct matching baselines solve a labeling problem, assigning each input vertex a matching index in a fixed template shape. Differently, 3D-CODED deforms a
fixed template and recovers correspondence by a nearest neighbor query for each input vertex using a one-sided Chamfer distance, as suggested in \cite{GFK+18}. Our method and FARM both require a complete shape as input, which we chose as the null pose of each of the test examples. Due to slow convergence and unstable behavior of FARM we only kept 20 useful matching results on which we report the performance. As seen in Figure 2.4, our method outperforms prior art by a significant margin. This result is particularly interesting since it demonstrates that even though we solve an alignment problem, which is strictly harder than correspondence, we receive better results than methods that specialize in the latter. At the same time, looking at the poor performance demonstrated by the other alignment-based methods, we conclude that simply solving an alignment problem is not enough and the details of our method and training scheme allow for a substantial difference. Qualitative correspondence results are visualized in the supplementary.

**AMASS Projections**

As FAUST is limited in variability, we further test our method on the recently pub-
Figure 2.4: Partial correspondence error, FAUST dataset. Same color dashed and solid lines indicate performance before and after refinement, respectively.

Figure 2.5: Partial correspondence error, AMASS dataset. Lished AMASS dataset. On the task of partial correspondence, we compare with FARM [MMRC18] and 3D-CODED [GFK+18a] for which code was available online. We report the correspondence error graphs in Figure 2.5. For evaluation we used 200 pairs of partial and full shapes chosen randomly (but consistently between different methods). Specifically, for each of the 4 subjects in AMASS test set we randomized 50 pairs of full poses: one was taken as the full shape $Q$ and one was projected to obtain the partial shape $P$, using the full unprojected version as the ground truth completion $R$. As with FAUST, we report the error curve of FARM taking the average of only the successful runs. As can be observed, our method outperforms both methods by a large margin. Qualitative correspondence results are visualized in the supplementary.

2.2.5 Real Scans

To evaluate our method in real-world conditions, we test it on raw measurements taken during the preparation of the Dynamic FAUST [BRPMB17] dataset. This use case nicely matches our setting: these are partial scans of a subject for which we have a complete reference shape at a different pose. As preprocessing we compute point normals for the
input scan using the method presented in [HDD+92]. The point cloud and the reference shape are subsequently inserted into a network pretrained on FAUST. The template, raw scan, and our reconstruction are shown, from left to right, in Figure 2.6. We show our result both as the recovered point cloud as well as the recovered mesh using the template triangulation. As apparent from the figure, this is a challenging test case as it introduces several properties not seen at test time: a point cloud without connectivity leads to noisier normals, scanner noise, different point density and extreme partiality (note the missing bottom half of the shapes). Despite all these, the proposed network was able to recover the input quite elegantly, preserving shape details and mimicking the desired pose. In the rightmost column, we report a comparison with Litany et al. [LBBM18]. Note that while [LBBM18] was trained on Dynamic FAUST, our network was trained on FAUST which is severely constrained in its pose variability. The result highlights that our method captures appearance details while pose accuracy is limited by the variability of the training set.
Chapter 3

Conclusion

We proposed an alignment-based solution to the problem of shape completion from range scans. Different from most previous works, we focus on the setting where a complete shape is given, but is at a different pose than that of the scan. Our data-driven solution is based on learning the space of distortions, linking scans at various poses to whole shapes in other poses. As a result, at test time we can accurately align unseen pairs of parts and whole shapes at different poses.
Appendix A

Extended Analysis

In this appendix we provide:

1. Further analysis of our network design
   - An ablation experiment demonstrating the improved reconstruction over a fixed template due to the full shape $Q$ in Section A.1.
   - Robustness analysis of our trained network in Section A.2.
   - An experiment exploring the network operation under different types of projections, resulting from elevated viewpoints, in Section A.3


3. Visualizations of the dense correspondence results from the partial shape to the full shape in Section A.5.

A.1 Comparison with a Fixed Template

As described in the main manuscript, in order to predict the completion of a partial shape $P$, our method requires a full reference shape $Q$ of the same subject in an arbitrary pose. We motivate this setting by a requirement for a completion that is faithful to the subject shape. This is different from previous completion methods which can only approximate or hallucinate missing details. Here we support this claim experimentally, by
Figure A.1: **Constant template used in ablation fixed-template experiment**

Comparing with a baseline that uses a fixed template. Specifically, instead of providing a full shape $Q$ of the same subject as the partial shape $P$, we provide a fixed template $T$ for all inputs. With this modification, the ablation network is trained with the triplets $\{(P_n, T, R_n)\}_{n=1}^N$, where $N$ is the size of the training set. At inference time, we use the same template $T$ to make a prediction for a given input part $P$. We chose the template to be the first subject from the FAUST Projections dataset, in its null pose as shown in Figure A.1. Both the original and the fixed-template networks were trained on the FAUST Projections training set, with identical parameters and for the same number of epochs, as described in Section 3.6 in the paper. Table A.1 summarizes the prediction errors of both methods, Figure A.3 compares the partial correspondence results and Figure A.2 shows visual comparison. The results clearly show the benefit of utilizing the shared geometry between the part and a full non-rigid observation of it. In particular, we receive a noticeable improvement in correspondence prediction as well as a lower reconstruction error across all metrics. Perhaps more importantly, Figure A.2 demonstrates the main motivation of our framework: a completion that respects the fine details of the underlying shape. To further emphasize this effect, we magnify the face regions of each shape, showing the loss in intricate details achieved with the alternative training method.

Figure A.2 implies how powerful our method is when it comes to the reconstruction of
fine details, such as the facial structure and delicate body features. We verify that acquiring access to a full observation in inference time can significantly improve the reliability of the reconstruction for a network trained to utilize such information. In the absence of this full observation at inference time, the ablation network can only utilize the input part and the acquired statistics of the training examples, encoded in the network weights. While this later information can be used for coarse completion, we evidence it is not sufficient for precise completion.
Figure A.2: **Comparison with fixed-template ablation experiment.** Our method recovers the shape details much more faithfully.
A.2 Robustness Analysis

We now turn to analyze the robustness and stability of our proposed method with regard to three important factors: Noise, sampling, viewpoint and proximity between the source and target poses. For this, we utilize a network trained on the FAUST train set and evaluate over a disjoint test-set of 200 single-view projected scans produced from 10 viewpoints of 2 subjects exhibiting 10 different poses. Each scan $P$ is matched with all possible poses $Q$ of the same subject, achieving a total of 2000 inputs. We utilize a descriptive partial set of the evaluation metrics proposed in section 4.2 of the paper to evaluate each experiment. Lastly, we examine how our network fares when we query for more complex deformations, depicting the averaged reconstruction errors over the azimuthal projection angles as a function of the L2 distance from the template and ground truth shapes.

Residual Noise

In this experiment, we attempt to emulate various artifacts commonly found in real depth scans. We corrupt the vertices of each partial input shape with various degrees of additive white Gaussian noise, with standard deviations in the range [0-4] cm. The corrupted partial shapes are fed to the network, together with the full shapes. Averaged reconstruction statistics are shown in Figure A.4 for a Euclidean and the two directional Chamfer distances. As can bee seen, our method accuracy only slightly declines with the increase of the noise.

Downsampling

We evaluate the network performance when provided with a partial shape at a lower resolution. For each partial shape in the test set, we decimate at random some percentage of the existing vertices. As can be seen in Figure A.5, even under a majority decimation of the vertices, the proposed network is able to recover well the ground truth shape.

Projection Angle

Finally, we examine the sensitivity of our network to the projection angle. We note that due to the different projection angles and poses, it is not unreasonable that some angles hold a higher degree of information relevant for reconstruction than others. Ideally,
Table A.1: **Comparison with Fixed-Template Ablation Experiment.** We evaluate our method against an ablation experiment, repeating exactly the same training except of one significant difference: instead of providing the full shape $Q_n$ as described in the main paper, we provided a constant full template $T$ in each of the training examples $\{(P_n, T, R_n)\}_{n=1}^{N}$. The template $T$ is used in inference as well, to predict the completion of a given input part $P$. We report the prediction errors on FAUST test set, while both networks were trained on FAUST train set. The first and second rows summarize the ablation errors and our method errors, respectively.

![Comparison with fixed-template ablation experiment. Partial correspondence error evaluated on FAUST Projections dataset.](image)

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gles projected from the ground truth shape. As seen in Figure A.7, the expected result is received, with the network losing accuracy when we query for more complex deformations.

### A.3 Handling Different Types of Partiality

We explored the performance of our network, operating on partial shapes resulting from different types of single view projections. Specifically, we repeated the training on FAUST dataset, sampling the projections uniformly in the azimuthal range of $[0, 360]$ and in the elevation range of $[-90, 90]$. This sampling produced a grid of 10 azimuthal and 11 elevation angles, resulting in 110 different projections per pose. Remarkably, this facilitated an improvement of 10%, on the solely azimuthally projected test-set reported in the main paper, reducing the error from 2.94 to 2.64 cm. When extending the test-set to infer on all 110 projections, we report an error of 2.78 cm, an improvement of 5.4% on a more challenging test-set. We hypothesize this improvement stems from a higher robustness due to the increased data augmentation.

### A.4 Additional Visualizations

Here we provide additional reconstructions that were not included in the main paper in order to save space. Figure A.8 and Figure A.9 visualize our network predictions for FAUST Projections and AMASS Projections datasets, respectively.

### A.5 Non-Rigid Partial Correspondence

Figure A.10 visualizes the dense correspondence between the input partial and full shape. As explained in the paper, we achieve this by using the network reconstruction as a proxy; For every point in the partial shape we calculate the nearest neighbor point in the reconstruction allowing us a recovery of a mapping between the partial shape to the reconstructed shape, which is by construction also the mapping between the part and the full input shape. In Section 4.4 of the paper we evaluated the predicted correspondence
numerically for FAUST Projections and AMASS Projections datasets, providing geodesic error graphs for both, in Figure 5 and Figure 6, respectively. For completion, we show the results also qualitatively here.
Figure A.4: Robustness to Noise. Three reconstruction metrics evaluated on completions originating from corrupted partial shapes with increasing levels of additive white Gaussian noise. A noise-free reference is marked with a dashed red line.
Figure A.5: **Robustness to Downsampling.** Three reconstruction metrics evaluated on completions originating from decimated partial shapes with varying levels of vertex erasure. A baseline with the evaluation realized with no decimation is marked with a dashed red line.
Figure A.6: **Robustness to Projection Angle.** Three reconstruction metrics evaluated on different groups of the test-set, partitioned by the projection angle. We note a close to uniform distribution over the different angles, attributing to a azimuthal invariancy.
Figure A.7: **Euclidean distance as a function of pose proximity.** Depiction of the reconstruction error received as a function of the vertex to vertex L2 distance RMSE of the template shape from the ground truth shape. Each dot represents a pair of template and ground truth shapes with the free variable being the distance RMSE between them, and the dependent variable a mean over the reconstruction errors received for the completion with each of the ten azimuthal angles. A linear trend line was fitted to the resulting points for orientation. As can be expected, the greater the deformation distance, the harder it is to deform the template shape to best fit the partial shape.
Figure A.8: **Predicted completions, FAUST Projections.** Each column shows a completion for a different subject, while each row provides a different perspective on the reconstructed 3D model. From left to right: full input shape $Q$, input part $P$, predicted completion $F_{\theta(P,Q)}(Q)$, ground truth completion $R$. 
Figure A.9: **Predicted completions, AMASS Projections.** Each column shows a completion for a different subject, while each row provides a different perspective on the reconstructed 3D model. From left to right: full input shape $Q$, input part $P$, predicted completion $F_{θ(P,Q)}(Q)$, ground truth completion $R$. 
Figure A.10: **Non-Rigid partial correspondence.** Left and right columns show the dense correspondence for FAUST Projections and AMASS Projections, respectively. From left to right: full input shape $Q$, our network completion $F_{θ(P,Q)}(Q)$ and partial input shape $P$. Corresponding points are indicated by the same color.
Bibliography


[RSK16] Elad Richardson, Matan Sela, and Ron Kimmel. 3D face reconstruction by learning from synthetic data. In 4th Int. Conf. on 3D Vision (3DV) Stanford University, CA, USA, 2016.


shall be obtained by completing the partial registration, and the remaining parts can be used to obtain the shape and size of the complete shape. The registration of a partial shape to a complete shape is a non-rigid partial registration (non-rigid partial registration) that is not an isometric transformation.

One of the methods in machine learning, especially deep learning, is widely used for various applications, such as object detection in images, which has become common in recent years, thanks to the ability of deep neural networks to represent continuous functions that are not necessarily known to be exact.

To guide the development of a formula to be applied in various cases, we propose a method that is both efficient and accurate for completing partial registration. The proposed method (Siamese autoencoder) is a deep neural network in a black-box form that does not require prior tagging of the points in the training set, and is therefore suitable for completing the missing points in a shape.

In our work, we propose a method that is both efficient and accurate for completing partial registration, given the geometry of the complete shape in the deformed position. The proposed method is based on learning from examples, and it takes advantage of the ability to approximate.

The proposed method demonstrates the efficiency and effectiveness of the method by applying it to the completion of shapes, even in dense and even in synthetic and real data. In all cases, we show improvements in the quality of the reconstruction compared to previous methods, and the visual results show the preservation of the unique features of the shape.

תקציר

זמיןות ומיחוד בר-הצגתה של חיות ייחודיותIW מואסף במאפיי שונים לקמדים את סריקתם של ידיס, מואסף
תופסיו. סריקת תלת-ממדית בערוץ החישון של כלול לרוב עגון של מלקות ומוני, החישון
יוצר בשנית נקודת בප הלאיםller חוסר של מלקות אחר. שלר ביסל אפילקטואות ארבאיה
מ늘이ות וסיקה של השולמות של כנף וקקונים. סיקורים שלמדים באמצעות (shape completion)
בהאבקות ובRails צויר משולמות של יעים, על מנת לשחזר את צורות המקוריות
הנמצאות בחללים המקוריות של יעים, על מנת לשחזר את צורות המקוריות
הנמצאות בחללים המקוריות של יעים, על מנת לשחזר את צורות המקוריות
הנמצאות בחללים המקוריות של יעים, על מנת לשחזר את צורות המקוריות
בניהם ברי alt מנותק של רוחות, קשיית ולא קשתות. צורות קשיאות כמי
מתנו את תנועות אנטי-🔄 וסיקריות בהם שב❄ות, סיקריות לבר
נמצאות לתمحطة אלקנרטיסי פסטואות כמי סיבוב, שיקוף זהו. מרחב השיכות שלר בחללח
百分百 שיש דרגות חוסר בלו, שנש עבורה מעיקות והארציות, שלוש עבורה וארוגנטית האוביקט
בשלושת העזר. לעתים ذات, צורות לא קשיאות כמי בו אדיא וחלק של מתנה למישחת המטרות רכבה
נעה בשמ איסומטריה (isometry), המטרות גם שמשורת בקורות אחרים את בייתなどが
نكודות של תנועה על כל הצורה. מתפר דרגות תופשות והנדישות לעצמאות של צורות אל ממרebb האוקלידי
התעלות ממיד, בודberos ממימה והציוניים של צורות קשיאות עלק כיקלד מרפק הנגף לרוב להשלות
אות התנועה הנשק במרחבי. עלק כ, בעיות השלימה של צורות אל הולות את גודל ופי של
צורות קシアט.

כאשר בוחנים את צורות התפרשות והיואה הלאים, אז ינוקות ילד זיפס חפיות מוזיאן שלון
מגיד קדוש משמעויות על הצורה אתראה סריטה על מתל אפול שלמה אנטי-יאלוב שסור
בגעיהז או ארמטקטוס בקורה שיש ב🍺 של שלמה צורות לא קשיאות (עלק הלאים תנועה
מתונה), במענה את האות ומטכין "שלמות שלר מודית”. בזאפוי מוקדם יותר, ביהנקר חיאברוסיריו
הממחקר בוצע בהנחייתו של פרופסור Ronnie Kimmel, בפקולטה למדעי המחשב.

חלק מה résultat המוצג הוא פריסתו כמאמרים מהמחבר ושוחרי המחברlassen בתוכי מס重点项目 ול]-$-

במהלך התקופה הממוסת על מחקר, אושר גרסאות הערדניות ביוור הי


אנימודהלטכניוןעלהתמיכההכספיתהנדיבהבהשתלמותי

אלגוריתמים עכשוויים עבור השלמה זרה מדינית

תיבובר על מחקר

לשם مليולי חלקי של הדורישה לקבלת התואר
מניסטר למופעי במדעי המחשב

ראידע עמנואל

מרגס לסנט טכנולוגית – מכון טכנולוגי לישראל
השוחט התשי"פ"ט חיפה אוקטובר 2021
אלגוריתמים עצביים עבורי השלבת יחדיו

עיידו עמנואל