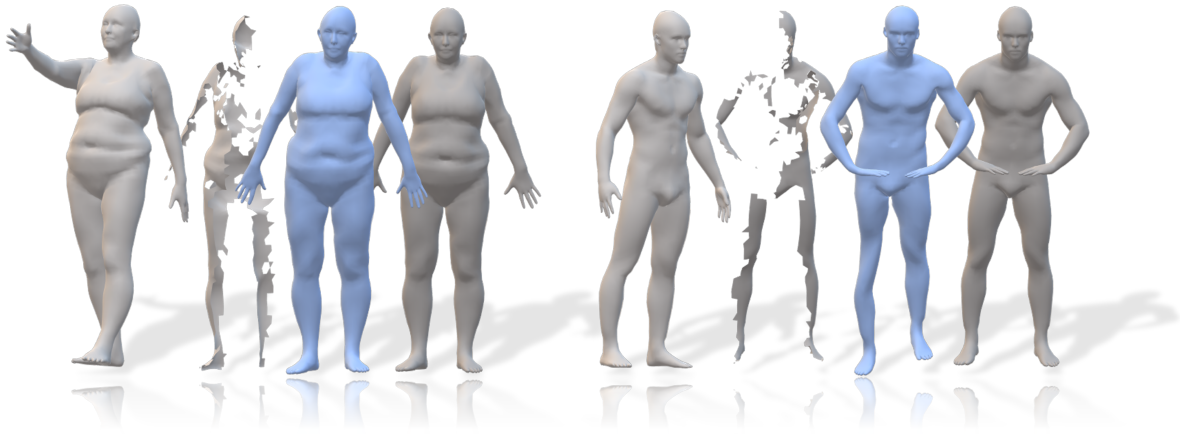
The Whole Is Greater Than the Sum of Its Nonrigid Parts



Left to right: input reference shape, input part, output completion, and the ground truth full model.

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Abstract

According to Aristotle, a philosopher in Ancient Greek, "the whole is greater than the sum of its parts". This observation was adopted to explain human perception by the Gestalt psychology school of thought in the twentieth century. Here, we claim that observing part of an object which was previously acquired as a whole, one could deal with both partial matching and pose reconstruction in a holistic manner. 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 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 on these tasks by a large margin.

1. Introduction

Aristotle, a philosopher in Ancient Greek announced that *"the whole is greater than the sum of its parts"*. This axiomatic observation was narrowed down to human perception of planar shapes by Gestalt psychology school of thought in the twentieth century.

From a practical perspective, advances in robotics and augmented and virtual reality technologies often rely upon the ability to render a scene from novel views, manipulate its content, and add physical constraints. This often requires the completion of geometric structures from partial data. To that end, we would like to have a systematic and universal way to complete a partial shape into its full counterpart, a problem frequently referred to as *shape completion* in the geometry processing community.

Shape completion is an ill-posed problem by definition, as one must address the question of what can be considered a legitimate completion. An attempt to answer this question can be addressed in a statistical manner. One can consider many instances of partial shapes and their corresponding completions, defining a statistical relation between a part and the geometric structure from which it was cropped, and by which the whole structure can be recovered in a statistically optimal manner.

In this paper, we introduce a *deterministic* shape comple-

tion framework. Given a partial observation, the method returns a reliable reconstruction of a full, realistic object. At a first glance, at least in a rigid setting, this task may seem impossible: How can we guarantee that such a reconstruction reliably describes the part that was hidden from the viewing direction? However, one soon realizes that the problem can be formulated differently in the *non-rigid* case. Since two non-rigidly related shapes could share the same intrinsic geometry [22, 14, 10], each shape holds information about the other. We therefore pose the alternative question: Given a full object Q and a partial view P *in a different pose*, can we reconstruct a *full* version of P by borrowing geometric information from Q? In this paper we address precisely this question. Our goal can thus be seen as a combination of two complementary tasks: (1) partial shape matching, and (2) non-rigid shape completion. While the two tasks are often addressed separately, we claim that considering their coupling provides powerful means to deal with both.

Contribution. In this paper we propose a novel formulation unifying deformable shape completion and partial shape matching. Specifically, given a full and a partial shape related by a non-rigid transformation, our objective is to deform the full shape to best fit the partial data. To compute this deformation, we train an encoder-decoder network. Once a completion for the part is predicted, the part-to-full correspondence can be trivially recovered using nearest-neighbor search. Our main contributions can be summarized as follows:

1. We introduce a deep Siamese architecture to tackle non-rigid alignment between a shape and its partial scan;

2. To the best of our knowledge, the proposed method is the first that addresses shape completion and partial correspondence in one framework under *extreme* partiality;

3. The proposed method is *efficient*, taking less than a second to provide both outputs without requiring any time-consuming post-processing steps.

2. Related work

Our problem setting is closely related to multiple research directions in the shape analysis and geometric deep learning communities. In an early attempt to use one pose in order to geometrically reconstruct another, Devir *et al*. [20] considered mapping a clean shape in a given pose onto the same noisy shape in a different pose . Elad and Kimmel were the first to treat shapes as metric spaces [21, 22]. In fact, it was the first approach of matching shapes by their spectra, specifically, second order moments of embedding the intrinsic metric into a Euclidean one via classical scaling. It involved comparing the spectra of the click's laplacian. Bronstein *et al*. [9, 10, 13, 8, 11, 14] dealt with partial matching of articulated objects in various scenarios, including pruning of the intrinsic structure while accounting for cuts.

Shape completion. Recovering a complete shape from partial measurements is a longstanding research problem that comes in many flavors. In the context of deformable shapes, early efforts focused on completion based on geometric priors [36] or reoccurring patterns [13, 38, 60, 40]. These methods are not suited for severe partiality. For such cases model-based techniques are quite popular, *i.e*., category-specific parametric morphable models that can be fitted to the partial data [4, 23, 44, 1]. Model-based shape completion was demonstrated for keypoint input [2], and was recently proven to be quite useful for recovering 3D body shapes from 2D images [65, 64, 28, 72]. Parametric morphable models [4], coupled with axiomatic image formation models were used to train a network to reconstruct face geometry from images [56, 55, 61]. Still, much less attention has been given to the task of fitting a model to a partial 3D point cloud. Recently, Jiang *et al*. [34] tackled this problem using a skeleton-aware architecture. However, their approach works well when full coverage of the underlying shape is given.

Deep learning of surfaces. Following the huge success of convolutional neural networks in images, in 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 [62, 68]. Another natural extension are 3D CNN on volumetric grids [69]. A host of techniques for mesh processing were developed as part of a research branch termed *geometric deep learning* [15]. These include graph-based methods [66, 67, 31], intrinsic patch extraction [47, 7, 48], and spectral techniques [41, 29]. Point cloud networks [52, 53] have recently gained much attention. Offering a light-weight computation restricted to sparse points with a sound geometric explanation [35], these networks have shown to provide a good compromise between complexity and accuracy, and are dominating the field of 3D object detection [51, 70], semantic segmentation [24, 71] and even temporal point cloud processing [17, 43]. For generative methods, recent implicit and parametric methods have demonstrated promising results [27, 49].

Inspired by the recent success of [26] in encoding non-rigid shape deformations using a point cloud network, here,

we also choose to use a point cloud representation. Importantly, while the approach presented in [26] 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.

Partial shape matching. Dense non-rigid shape correspondence [37, 16, 41, 30, 58, 12, 18] 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. This setting has been tackled with moderate success in a few recent works [57, 42, 54], 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.

3. Method

3.1. 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 can carry additional semantic or geometric information encoded as feature vectors.

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 $F : \mathbb{R}^3 \to \mathbb{R}^3$ aligning Q to P[1]. 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 $F(Q) = R$. 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 as well.

Clearly, the deformation function F depends on the input pair of shapes (P, Q). We model such dependency by considering a parametric function $F_\theta : \mathbb{R}^3 \to \mathbb{R}^3$, where θ 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.

Our network is composed of an encoder E and a generator F_θ. The encoder takes as input the pair (P, Q) and embeds it into a latent code θ. To map points from Q to their new location, we feed them to the generator along with the latent code. In what follows we first describe each module, and then give details on the training procedure and the loss function. We refer to Figure 1 for a schematic illustration of our learning model.

[1] In our setting, we assume that the pose can be inferred from the partial shape (*e.g.*, an entirely missing limb would make the prediction ambiguous), hence the deformation function F is well defined.

3.2. Encoder

We propose the adoption of a Siamese pair of encoders, each producing a global shape descriptor (respectively θ_{part} and θ_{whole}). The two codes are then concatenated so as to encode the information of the specific pair of shapes, $\theta = [\theta_{part}, \theta_{whole}]$.

Our choice for the internal architecture in the Siamese pair is based on a preliminary ideal requirement: the encoder should *injectively* map each pair of shapes into a latent code. In other words, we require that each shape should be accurately reconstructed from its latent code. This requirement guarantees that for a fixed full shape Q and two different parts P_1 and P_2, there would be a way to deform the full shape differently by using $\theta(P_1, Q)$ or $\theta(P_2, Q)$, based on the input part.

Motivated by existing methods [27, 26], we use a PointNet-3DCODED architecture for our encoder. Specifically, each encoder within the Siamese pair applies a multilayer perceptron to each 3D point of the input shape, with hidden dimensions $(64, 128, 1024)$, followed by a max-pool operation over the input points, leading to a 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 $\theta_{whole}, \theta_{part}$ of size 1024 respectively, supplying a representation of the pair by a latent code θ of size 2048.

In practice, we find it helpful to also use the normal vector coordinates as additional input features to each of the Siamese network encoders, making each input point a 6D point. The rationale behind this choice is that, by doing so, we are able to disambiguate contact points of the surface and thus to prevent contradicting requirements on the deformation function.

3.3. Generator

Given the code θ representing the partial and full shapes, the generator has to predict the deformation function F_θ to be applied to the full shape Q. We realize F as a multi-layer perceptron (MLP) to approximate the functional relation between an input point q_i on the full shape Q, and the corresponding output point r_i on the ground truth completed shape. The multi-layer perceptron operates pointwise on each tuple (q_i, θ), where the shape context θ is kept fixed for each input pair. 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 $(2054, 1024, 512, 256, 128, 128, 128, 128, 3)$, followed by hyperbolic tangent activation function.

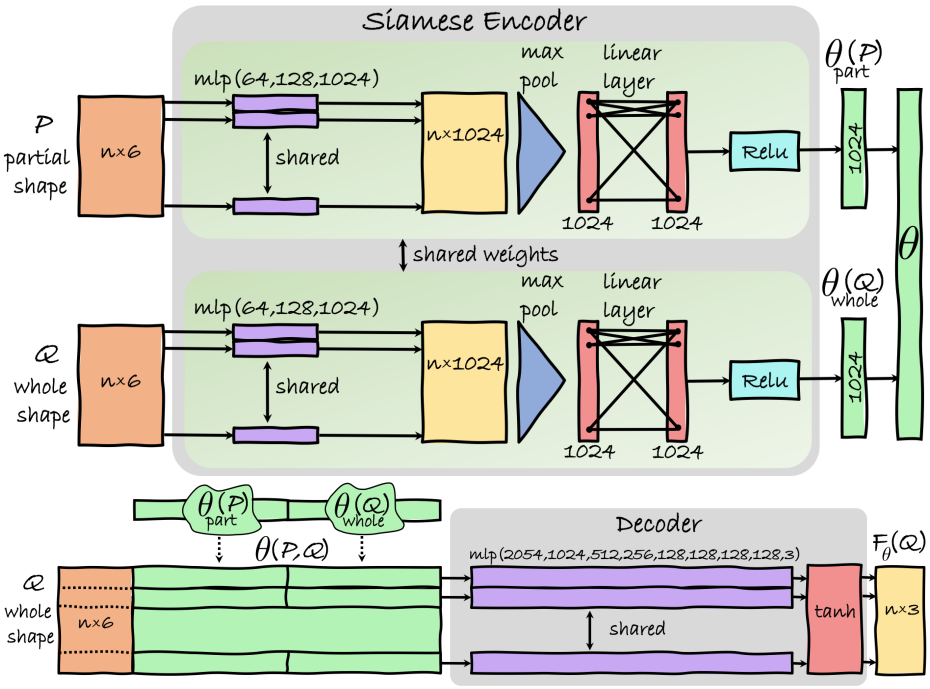

Figure 1. Siamese encoder architecture at the top, and the decoder (generator) architecture at the bottom. A shape is provided to the encoder as a list of 6D points, representing the spatial and unit normal coordinates. The latent codes of the input shapes $\theta_{part}(P)$ and $\theta_{whole}(Q)$ are concatenated to form a latent code θ representing the input pair. Based on this input pair, 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_θ(Q).

3.4. Training Procedure

In our experiments we used training examples that were prepared from datasets of full human shapes, see details in the data preparation section 4.1. Each of these datasets contain 3D models of different subjects in various poses. Each of our training examples is composed of a triplet (P, Q, R): a partial shape P, a full shape in a different pose Q and a ground truth completion R. The shape Q and R were sampled from the same subject in two different poses. In each training example, the partial shape P is extracted from R by rendering its depth map in a random viewpoint angle, with the azimuth changing between $0°$ and $360°$ and the elevation angle kept at $0°$. These synthetic projections aim to approximate partiality realizations commonly occurring in depth sensors. By their nature, these partial shapes still hold most of the information needed to determine the degrees of freedom w.r.t the pose, making the pose reconstruction a well-posed problem. 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 $F_{\theta(P_n,Q_n)}(Q_n)$. This reconstruction is subsequently compared against the ground-truth reconstruction R_n using the loss defined in the next subsection 3.5.

3.5. Loss function

Essentially, the loss definition should reflect the visual plausibility of the reconstructed shape. Measuring such a quality analytically is a difficult problem. In this paper we adopt a naive measurement based on the Euclidean proximity between the ground-truth and the reconstruction. Formally, we define the loss as,

$$\mathcal{L}(P, Q, R) = \sum_{i=0}^{n_q} \left\| F_{\theta(P,Q)}(q_i) - r_i \right\|^2, \qquad (1)$$

where $r_i = \pi^*(q_i) \in R$ is the ground-truth matched point of $q_i \in Q$, and $\pi^* : Q \to R$ is the ground-truth mapping between the full shape Q and the ground-truth reconstruction R. To promote the preservation of shape details we measure the Euclidean distance between the coordinates in $\mathbb{R}^3$ as well as the Euclidean distance between the normal vectors evaluated at each point, interpreting q_i and r_i in the expression above as points in $\mathbb{R}^6$. Specifically, $q_i = (\vec{x}_{qi}, \alpha\vec{n}_{qi}), r_i = (\vec{x}_{ri}, \alpha\vec{n}_{ri}) \in \mathbb{R}^6$ are given by the concatenation of the coordinates vectors and the unit normal vector of each point in Q and R, respectively. The constant $\alpha > 0$ scales the normal vectors w.r.t. the Euclidean coordinates. The notation $\vec{n}_{qi}$ denotes the normal of the surface Q at point q_i, while $\vec{x}_{qi}$ denotes the coordinates of that point in $\mathbb{R}^3$. Similarly, $\vec{n}_{ri}$ denotes the normal of the surface R at

point r_i, while $\vec{x}_{ri}$ denotes the coordinates of that point in $\mathbb{R}^3$.

The above loss may be refined for better preserving visual appearance. Among the possible reconstructions that admit a low value for $\mathcal{L}$ one could find two shapes where one achieves a lower $\mathcal{L}$ value while the other looks more realistic. The reason is that even though the parts were chosen such that most degrees of freedom for the possible completion w.r.t. pose are determined, still, the exact details such as the accurate position and orientation of missing regions are under-determined. Therefore, there is a narrow margin of acceptable completions in the adjacency of the provided ground-truth shape, implying that the Euclidean proximity is measured w.r.t. to an arbitrary anchor. While for small values of $\mathcal{L}$ the correlation between the loss and the reconstruction quality is indefinite, for high values there is a strong correlation between the suggested loss and realism. Empirically, we observed that this loss's convergence produces high quality reconstructions.

3.6. Implementation considerations

The network was trained with each batch containing 10 triplet examples (P, Q, R), using the PyTorch [50] ADAM optimizer with a learning rate of 0.001 and a momentum of 0.9. We used a scale factor of $\alpha = 0.1$ for the normal vector. The network was trained for 50 epochs, each containing $10,000$ random triplet examples. The input shapes were translated such that their center of mass lies at the origin and the Iterative Closest Point algorithm [3] was further applied on the network output to perfectly align the axes w.r.t. the partial shape. Finally, to calculate the partial correspondence for each point in the partial shape, we retrieve its nearest-neighbor in the aligned reconstruction.

4. Experiments

The proposed method simultaneously tackles two important tasks in nonrigid shape processing and analysis, shape completion and partial shape matching. We emphasize that the suggested framework gracefully handles severe partiality. Prior efforts either addressed one of these tasks or attempted to address both only at mild partiality conditions. To thoroughly evaluate our performance, in this section we test our method on each of these tasks and compare with prior art. After a description of the datasets utilized, we present results of shape completion from a single view , and non-rigid partial correspondence. Finally, we show performance on real scanned data.

4.1. Datasets

We utilize two datasets of human shapes for training and evaluation, FAUST [5] and AMASS [45]. Both datasets were generated by fitting SMPL parametric body model [44] to raw scans. The second took the approach one step further by fitting those parameters to motion capture data. These datasets are quite different in size and variability. FAUST is a relatively small set of 10 subjects posing at 10 poses each. We follow previous methods, and test our method in partial shape matching and shape completion tasks using 10 projected views of these models. AMASS is currently the largest and most diverse dataset of human motion designed specifically for deep learning applications. It was generated by curating 15 archived datasets of marker-based optical motion capture data and unifying them into a shared statistical model SMPL+H [59]. As such, it can provide a much richer resource for evaluating the generalization ability of shape alignment and matching techniques. To this end, we used AMASS to create a large set of single-view projections. Specifically, we sampled every 100th frame from all provided sequences and rendered single-view projections from 10 equally spaced azimuth angles (elevation was kept fixed) using pyRender [33]. Keeping the original data splits our dataset consists a total of 110K, 10K, and 1K full shapes for train, validation and test, respectively; and 10 times that size for the partial shapes. Note that at train time we randomly mix and match full shapes and their parts which drastically increases the effective set size.

4.2. Methods in comparison

A recent exploration of the problem of deformable shape completion for arbitrary partiality can be found in Litany *et al*. [39]. They suggest to find a completion via optimization in a learned shape space. Note that in that paper, the task was defined as a completion from a partial view without explicit access to a full model. Moreover, their solution requires a preliminary step of running a partial shape matching algorithm, which is slow due to the optimization at inference time. 3D-CODED [26] performs a template based alignment to an input shape in two stages: fast inference and a slow refinement through optimization. It is designed for pairs which are either full or witness to mild partiality, hence, to make the comparison more meaningful we adjust their loss at the refinement phase to the more suited directional Champfer distance. FARM [46] is also an alignment-based solution which has shown very impressive results on shape completion and dense correspondences. It builds on the SMPL [44] 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. 3D-EPN [19] is a rigid shape completion method based on a voxelization approach, utilizing a 3D CNN. Results are converted to a mesh via computation of an isosurface. A classic Poisson reconstruction [36] is also provided as a naïve baseline with no access to additional data other than the partial input.

4.3. Evaluation metrics

As previously discussed, it is challenging to define an analytic measurement for completion quality. Therefore we provide 5 different measurements, each reflecting a different perspective of the final completion as summarized in tables 1,2. First we report the mean square error (MSE) of the Euclidean distance between each point in the reconstructed shape and its ground truth mapping. This measure is reported only for template alignment methods for which the correspondence between the template and the ground truth reconstruction is defined. Next, we report the MSE of directional Chamfer distances: from the ground-truth to the completion and vice versa; The former measures the coverage of the ground-truth shape by the completion while the later penalizes outliers of the completion; We report the sum of both as full the Chamfer distance. Finally we measure the absolute error in the volume of the completion divided by the volume of the ground truth as a measure for volume deformation.

4.4. Single view completion

We evaluate the proposed method on the task of deformable shape completion on two datasets: FAUST and AMASS.

FAUST projections We follow the evaluation protocol proposed in [39] and summarize the completion results of our method and prior art in Table 1. As can be seen our network performs a much more accurate completion. Especially note the small standard deviation in the volumetric error that reflects our network has learned to keep the appearance of the input full shape. Contrary to optimization based methods [39, 25, 46] which are very slow at inference time, our feed-forward network performs inference in less than a second. To better appreciate the quality of our reconstructions, in Figure 3 we visualize several completions attained with various methods. Note the accurate preservation of intricate details which were completely lost in previous methods.

AMASS projections Using our generated set of partial shapes from AMASS described in 4.1, we compare our method with two recent methods based on shape alignment: 3D-CODED [26], and FARM [46]. As described in 4.2, 3D-CODED is based on a fixed template, and is not trained to handle severe partiality. It thus serves as a lower bound for our proposed method. FARM, on the other hand, was build for the same setting as ours. We summarize the results in Table 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. Particularly interesting is the large error and tiny standard deviation for 3D-CODED. This reflects the flattened results with consistently poor volumetric measure. Visualizations of several completions are shown in Figure 2.

4.5. Non-rigid partial correspondences

Finding dense correspondences between a full shape and its deformed parts is still a very much open 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 the correspondence by a simple nearest neighbour search. As before, we evaluate this task on both FAUST and AMASS data.

FAUST projections On the FAUST projections dataset, we compare with both alignment-based methods, FARM and 3D-CODED, as well as 3 methods designed to directly recover correspondences, i.e. without recovering the alignment: MoNet [48], and two 3-layered Euclidean CNN baselines, trained on either SHOT [63] descriptors or depth maps. Results are reported in Figure 4. The test set consists of a total of 200 shapes: 2 subjects at 10 different poses and 10 projected views. The direct matching baselines solve a classification problem for each shape vertex to a template shape. Differently, 3D-CODED has its own template used at train time. Note that since 3D-CODED was not build for severe partiality, we adjust its loss to a one-sided Chamfer distance in the refinement stage. Our method and FARM both require a complete shape, 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 can be seen from Figure 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 a strictly harder problem 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, 3D-CODED and FARM, 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.

4.6. Real scans

To evaluate our method in real world conditions, we test it on raw measurements taken during the preparation of the Dynamic FAUST [6] 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. We pre-process the input point cloud by extending it with estimation of its point normals using the method presented in

Error	Euclidean distance GT and reconstruction [cm]	Volumetric err. mean $\pm$ std [%]	Directional Chamfer distance GT to reconstruction [cm]	Directional Chamfer distance reconstruction to GT [cm]	Full Chamfer distance [cm]
Poisson [36]	23.73	24.8 ± 23.2	7.3	3.64	10.94
3D-EPN [19]	23.5	89.7 ± 33.8	4.52	4.87	9.39
3D-CODED [25]	35.50	21.8 ± 0.3	11.15	38.49	49.64
FARM [46]	35.77	43.08 ± 20.4	9.5	3.9	13.4
Litany *et al*. [39]	7.07	9.24 ± 8.62	2.84	2.9	5.74
Ours	**2.94**	$\mathbf{7.05 \pm 3.45}$	**2.42**	**1.95**	**4.37**

Table 1. **FAUST Shape Completion**. Comparison of different methods with respect to errors in vertex position and shape volume.

Error	Euclidean distance GT and reconstruction [cm]	Volumetric err. mean $\pm$ std [%]	Directional Chamfer distance GT to reconstruction [cm]	Directional Chamfer distance reconstruction to GT [cm]	Full Chamfer distance [cm]
3D-CODED [25]	36.14	$\mathbf{14.84 \pm 8.02}$	13.65	35.35	49
FARM [46]	27.75	49.42 ± 29.12	11.17	5.14	16.31
Ours	**6.58**	27.62 ± 15.27	**4.86**	**3.06**	**7.92**

Table 2. **AMASS Shape Completion**. Comparison of different methods with respect to errors in vertex position and shape volume.

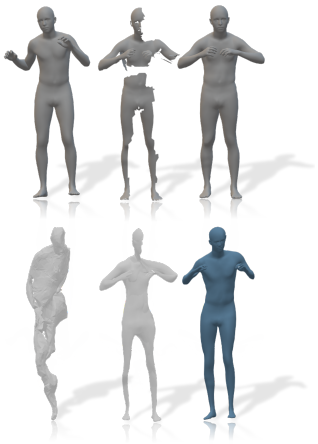

Figure 2. **AMASS Shape Completion** . At the top from left to right: full shape Q, partial shape P, ground truth completion R. At the bottom from left to right: reconstructions of FARM [46], 3D-CODED [25] and our own.

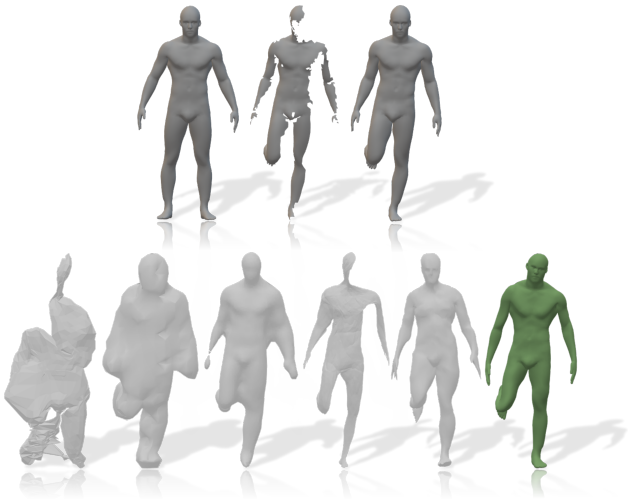

Figure 3. **FAUST Shape Completion** . At the top from left to right: full shape Q, partial shape P, ground truth completion R. At the bottom - reconstructions from FARM [46], 3D-EPN [19], Poisson [36], 3D-CODED [26], Litany *et al* [39] and our own.

[32]. 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 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, our 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*. [39]. Note that while [39] was trained on Dynamic FAUST, our network trained on FAUST which is severely constrained in its pose variability. The result highlights that our method favors realism and details in appearance over pose accuracy.

5. Concluding remarks

We have demonstrated that the problem of partial matching can be treated in a holistic manner when trying to fit a given part to a whole restricted to the pose inflicted by the part. By encoding the space distortion linking between parts at various poses to whole shapes given in other poses, we have been able to train a network to consider couples of parts and shapes at different poses, and match each part

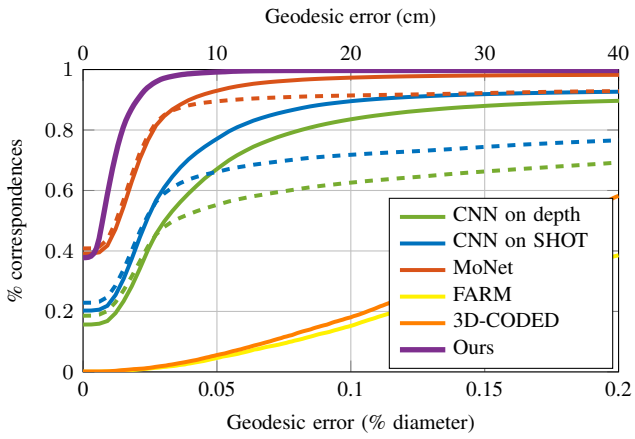

Figure 4. Generalization error on the FAUST dataset. Dashed line and solid line in the same color indicate performance before and after refinement, respectively. Note that our method doesn't require refinement, contributing to its computational speed.

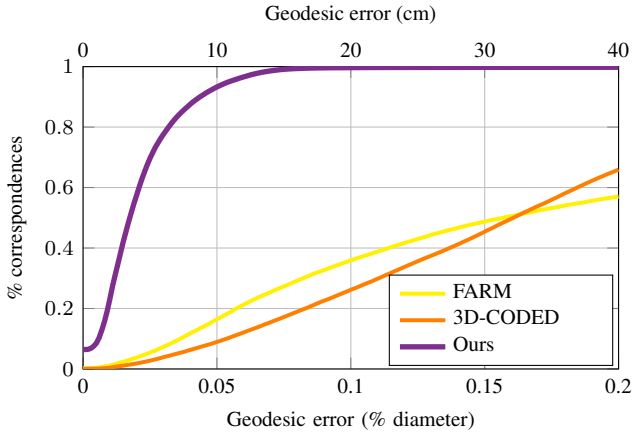

Figure 5. Generalization error on the Amass dataset

to its whole. This was realized by deforming the embedding space such that a resulting new whole shape aligns with, while obtaining the pose of, the given part. From Ancient Greek holistic philosophy, through modern psychology explanations of the human brain perception of shapes, we have demonstrated that computational matching procedures could benefit from the same axiomatic assumption stating that indeed *the whole is larger than the sum of its parts*.

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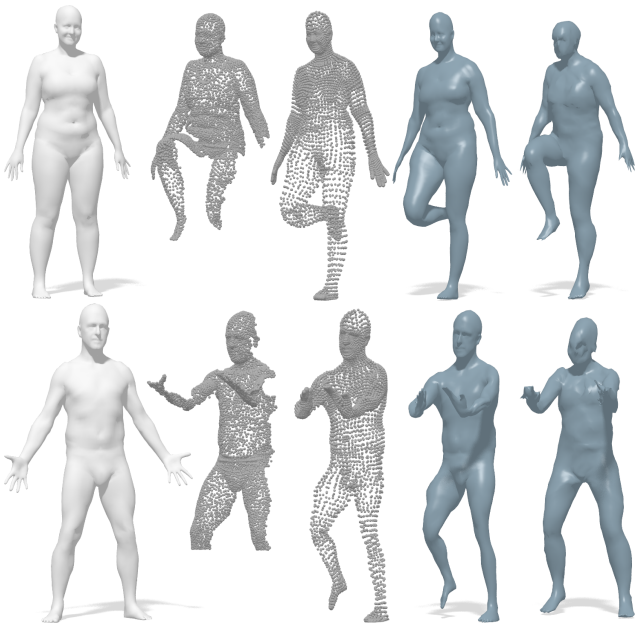

Figure 6. Completion from real scans from the Dynamic Faust dataset[6]. From left to right: Input reference shape; input raw scan; our completed shape as a point cloud; and as mesh; completion from Litany *et al*. [39].

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