Abstract

Learning based representation has become the key to the success of many computer vision systems. While many 3D representations have been proposed, it is still an unaddressed problem for how to represent a dynamically changing 3D object. In this paper, we introduce a compositional representation for 4D captures, i.e. a deforming 3D object over a temporal span, that disentangles shape, initial state, and motion respectively. Each component is represented by a latent code via a trained encoder. To model the motion, a neural Ordinary Differential Equation (ODE) is trained to update the initial state conditioned on the learned motion code, and a decoder takes the shape code and the updated pose code to reconstruct 4D captures at each time stamp. To this end, we propose an Identity Exchange Training (IET) strategy to encourage the network to learn effectively decoupling each component. Extensive experiments demonstrate that the proposed method outperforms existing state-of-the-art deep learning based methods on 4D reconstruction, and significantly improves on various tasks, including motion transfer and completion.

1. Introduction

Shape representation is one of the core topics in 3D computer vision, especially in the era of deep learning. Early work uses explicit representation, e.g. volume [13, 17, 58], point cloud [46, 16, 45, 1], and mesh [18, 23, 57] for 3D related tasks, such as shape reconstruction, synthesis, and completion. Recently, deep implicit representation [33, 40, 22] shows promising performance in producing accurate geometry with appealing surface details. However, arguably, we, humans, stay in a 3D world with an additional temporal dimension, and the majority of data we perceive everyday are moving or deforming 3D objects and scenes. Many existing applications also require understanding or reconstruction of 4D data, such as autonomous driving, robotics, and virtual or augmented reality. But the deep representation for 4D data, i.e. a deforming 3D object over a time span, is barely missing in the literature. As a pioneer work, Niemeyer et al. [37] propose to predict velocity field of the 3D motion via a Neural ODE [11]. However, the method mainly focuses on recovering and integrating local flow for 4D reconstruction, which might accumulate error and thus produce sub-optimal quality.

In this work, we propose a novel deep compositional representation for 4D captures. This representation not only can be used to reconstruct 4D captures, but they also extract key understanding that supports high-level tasks, such as motion transfer, shape completion, or future prediction. This is achieved by an encoder that takes a 4D capture as input and produces latent codes representing the geometry template, initial state, and temporal deformation respec-
atively. Taking human as an example, these three key factors are commonly understood as the identity, initial body pose, and motion\textsuperscript{1}.

To reconstruct the 4D capture, we design a novel architecture taking three latent codes as inputs. First, we keep the geometry template code (i.e., the identity) unchanged over time since it is not affected by the motion. Then, we propose a novel conditional latent Neural ODE \cite{11} to update the initial state code (i.e., the initial body pose) conditioned on the deformation code (i.e., the motion). The temporally varying state code is further concatenated with the geometry template code, and fed into a decoder to reconstruct an implicit occupancy field for each time frame, which recovers the 3D shape over time. Mostly similar to us, Occupancy Flow \cite{37} also use Neural ODE \cite{11} to update the position of each 3D point for 4D reconstruction. In contrast, our method applies the Neural ODE to update the latent state code that control the shape globally, which is empirically more stable.

To learn our compositional representation, we propose a training strategy to enable the encoder to decouple the geometry template and deformation, inspired by He et al. \cite{19}. Specifically, we take two 4D captures from different subjects and extract their latent codes respectively. We then swap their geometry template code and train the network to reconstruct the motion with swapped geometry template. The training is fully supervised by synthetic data, where parametric model is used to generate 4D captures with the same motion but different geometry template, e.g. SMPL model \cite{28} for human. We found this training strategy is effective in separating geometry template from the motion, which naturally supports motion transfer. The representation also enables 4D completion from captures with either missing frames or partial geometry by solving an optimization to update the latent codes until the partial observation is best explained.

Our contributions can be summarized as follows. First, we design a novel deep representation for 4D captures that understands the geometry template, initial state, and temporal deformation, and propose a novel training strategy to learn it. Second, we propose a novel decoder to reconstruct 4D captures from the learned representation, which includes, as a key component, a conditional Neural ODE to recover varying pose codes under the guidance of the motion code; and these codes are then translated into an occupancy field in implicit representation to recover the varying shape. Finally, we show that our model outperforms state-of-the-art methods on 4D reconstruction, and our compositional representation is naturally suitable for various applications, including motion transfer and 4D completion.

\textsuperscript{1}Since the experiment is mainly conducted on 4D human captures, we use these terms interchangeably.

2. Related Work

There is a large body of work that focuses on 3D representations, 4D captures and 3D pose transfer. We discuss the most related techniques in the context of our work.

3D Representation

There has been a lot of work aiming at reconstructing a continuous surface from various type of inputs, such as color images \cite{49, 57, 25, 10, 38}, point clouds \cite{7, 3, 26}, etc. Recently, great success has been achieved for 3D shape reconstruction using deep learning techniques. In early works, 3D volumes \cite{13, 17, 58} and point clouds \cite{46, 16, 45, 1} are adopted as the outputs of the networks, which suffer from the problems of losing surface details or limited resolutions. With the development of the graph convolution network, many recent methods \cite{18, 23, 57, 27} take the triangle mesh as the output representation, most of which regress the vertices and faces directly and require initial template and fixed topology. Most recently, there has been significant work \cite{33, 40, 22, 12, 15, 8} on learning an implicit field function for surface representations, which allow more flexible output topology and network architectures. Among those methods, Occupancy Networks \cite{33} represent the shapes using continuous indicator functions by specifying which subset of 3D space the shapes occupy, and the isosurface can be extracted by utilizing marching cube algorithms \cite{29}, which are adopted as the 3D decoder backbone for our network.

4D Capture

Research on 4D capture has been advancing significantly in the past decades \cite{42, 53, 32, 2}. However, most works are developed based on strong assumptions \cite{54, 42, 53, 31, 56}, demand the costly multi-view inputs \cite{36, 52, 35, 14}. Behl et al. \cite{4} provide the 4D scene flow estimation leveraging object localization or semantic priors from deep networks, while the motion of scenarios is assumed to be in a tiny range, fixed pattern, rigid or linear, and high quality multi-view inputs are required. This greatly limits the ease of use and stability. Meanwhile, some methods exploit guided transformations on predefined templates to capture the time-dependent 3D flow \cite{5, 28, 60, 43, 24}. Such methods usually focus on specific shape categories and the performance is restricted by the characteristic and generalization ability of the template model.

Recently, Occupancy Flow \cite{37} is presented to learn a temporally continuous field to model the motion of every point in space and time with Neural ODE \cite{11} and the continuous 3D occupancy representation. Nevertheless, since the network is trained to model the continuous flow of the initial occupancy space, the quality of 4D reconstruction results relies on the initial frame heavily.

3D Pose and Motion Transfer

Conventional methods solving the 3D pose transfer problem via discrete deformation transfer. Learning-based mesh deformation is presented
Compositional/Disentangled Representation Learning compositional/disentangled representations has been extensively studied in previous work [51, 34, 48, 61, 41, 50]. One attractive property of human intelligence is to learn novel concepts from a few or even a single example by composing known primitives [51], which is lacking in current deep learning system. Prior work utilize compositional/disentangled representations to address various tasks. Zhu et al. [61] disentangle shape, viewpoint, and texture and present an end-to-end adversarial learning framework to generate real images. Tewari et al. [50] learn a face model from in-the-wild video with a novel multi-frame consistency loss, the proposed approach represent the facial geometry and appearance in different spaces and achieve realistic 3D face reconstruction. Park et al. [41] propose a fully unsupervised method to learn an swapping autoencoder for deep image manipulation tasks, which disentangles texture from structure. Most recently, CaSPR [47] learns a 4D representation of dynamic object point cloud sequences in Temporal-NOCS using latent Neural ODE and enables multiple applications. By dividing the latent feature into static and dynamic parts, it realizes shape and motion disentanglement. Unlike methods mentioned above, our goal is to learn a deep compositional representation for 4D captures with conditional latent Neural ODE, which decouples geometry template, initial state, and temporal deformation in different latent spaces and supports various high-level tasks.

Figure 2: Overview of our model. Our full model contains three building blocks, namely, compositional encoder, latent pose transformer and implicit occupancy decoder. During each training step, two point cloud sequences are chosen randomly from the training set as a pair and fed into the three encoders successively (note the motion encoder is provided with the full sequence, while the other two encoders are only provided with the first time step of sequence). After that, there is a certain probability that the identity codes of the two sequences are exchanged before continuing the forward propagation. Note that if the identity codes are exchanged, the ground truth mesh used for loss calculation will also be updated correspondingly.

in [55], which leverages the novel spatially adaptive instance normalization [21] in the deep network. Nevertheless, dense triangle mesh is required and the modeling of both spatial and temporal motion continuous flow is unavailable.

3D motion transfer aims to producing a new shape sequence given a pair of source and target shape sequences, making the target shape sequence do the same temporal deformation as the source, which focuses on the continuous pose transformation among shape sequences. By applying vector field-based motion code to target shape, Occupancy Flow [37] transfers motion among human model sequences. Essentially, since Occupancy Flow does not explicitly disentangle the representations of poses and shapes as done in our work, we notice the good motion transfer results of Occupancy Flow are mostly achieved in the cases that the identities from source and target have similar shapes.

Loss Calculation

Input Sequences
Compositional Encoder
Latent Codes
Latent Pose Transformer
Implicit Occupancy Decoder
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Compositional/Disentangled Representation Learning compositional/disentangled representations has been extensively studied in previous work [51, 34, 48, 61, 41, 50]. One attractive property of human intelligence is to learn novel concepts from a few or even a single example by composing known primitives [51], which is lacking in current deep learning system. Prior work utilize compositional/disentangled representations to address various tasks. Zhu et al. [61] disentangle shape, viewpoint, and texture and present an end-to-end adversarial learning framework to generate real images. Tewari et al. [50] learn a face model from in-the-wild video with a novel multi-frame consistency loss, the proposed approach represent the facial geometry and appearance in different spaces and achieve realistic 3D face reconstruction. Park et al. [41] propose a fully unsupervised method to learn an swapping autoencoder for deep image manipulation tasks, which disentangles texture from structure. Most recently, CaSPR [47] learns a 4D representation of dynamic object point cloud sequences in Temporal-NOCS using latent Neural ODE and enables multiple applications. By dividing the latent feature into static and dynamic parts, it realizes shape and motion disentanglement. Unlike methods mentioned above, our goal is to learn a deep compositional representation for 4D captures with conditional latent Neural ODE, which decouples geometry template, initial state, and temporal deformation in different latent spaces and supports various high-level tasks.
3. Method

In this section, we introduce our compositional representation for 4D captures and the training strategy to learn it from data. The full pipeline of our framework is illustrated in Fig. 2. Taking a 3D model doing non-rigid deformation in time span $[0,1]$, we extract the sparse point cloud from the 3D model in $K$ uniformly sampled time stamps and feed them to the network as inputs. Our goal is to learn separate compact representations for identity $c_i$, initial pose $c_p$, and motion $c_m$, and reconstruct the 3D model at any continuous time stamp from them. On the encoder side, we train three PointNet [46] based networks to extract compact representations for identity $c_i$, initial pose $c_p$, and motion $c_m$, and reconstruct the 3D model in $K$ uniformly sampled time stamps and feed them to the network as inputs. To reconstruct mesh in target time $t$, we first update the initial pose code $c_p$ to $c_p^{(t)}$ encoding the pose of the 3D model in target time, which is achieved via a Neural ODE [11] conditioned on motion code $c_m$. The $c_i$ and $c_p^{(t)}$ are then concatenated and fed into a network to produce an implicit occupancy field indicating whether a 3D location is inside or outside the 3D shape, and the 3D mesh surface can be reconstructed via the Marching Cube algorithm [30].

3.1. Compositional Encoder

We utilize three separate encoders to extract 128-d latent codes for the identity, pose, and motion respectively. Inspired by Occupancy Flow [37], we use a PointNet-based [46] network architecture with ResNet blocks [20] as the backbone, although the input to each encoder is different according to the semantic meaning of each code. The initial pose only depends on the 3D shape in the first frame, therefore the corresponding encoder only takes the point cloud of the first frame, i.e. $t = 0$, as input. In contrast, the motion encoder takes the whole point cloud sequence as the input since the motion code needs to encode the deformation throughout the whole time span. To get the identity code, the encoder can take the whole sequence as input, but we empirically found that using only the first frame is enough and achieves similar performance.

3.2. Latent Pose Transformer

After obtaining the $c_i$, $c_p$, and $c_m$ from the compositional encoder, the next step is to update the pose code for target time $t$, i.e. $c_p^{(t)}$, which are used to reconstruct the 3D shape in corresponding time stamp. Intuitively, the target pose code should start from the initial pose code, i.e. $c_p^{(t=0)} = c_p$, and varies continuously over time conditioned on the motion code $c_m$. To this end, we propose a novel latent pose transformer, which is achieved by a conditional latent Neural ODE.

Neural ODE is used to reconstruct continuous temporal signals $S(t)$. Instead of directly estimating the target value, Neural ODE $f_\theta(t)$ predicts differential elements at each time stamp, which can be integrated to reconstruct the signal, i.e. $S(T) = S(0) + \int_0^T f_\theta(t, S(t)) \, dt$. For our specific scenario, we train a Neural ODE to predict the variation of the latent pose code over time. Different from original Neural ODE, our model is further conditioned on the motion code, which allows the same network to update initial poses in different manners according to the motion exhibit in the input sequence. Therefore, the pose code in target time $T$ is obtained by

$$c_p^{(T)} = c_p + \int_0^T f_\theta(c_p^{(t)}, t \mid c_m) \, dt,$$

where $f_\theta(\cdot)$ is modeled by a neural network of 5 residual blocks with $\theta$ as the parameters. Follow the advice of [11], we obtain the gradient using the adjoint sensitivity method [44]. For more details, please refer to the Supplementary Materials.

3.3. Implicit Occupancy Decoder

The last stage of our model translates the identity code $c_i$ and the pose code in target time $c_p^{(t)}$ into 3D shape. Inspired by high geometry quality from recent work using implicit representation [40, 33, 59], we train an Occupancy Network (ONet) [33] to predict for each 3D location if they were inside or outside the object surface:

$$o_p^{(t)} := \Phi_\eta(p \mid c_i \oplus c_p^{(t)}),$$

where $p$ is a 3D location, $\Phi_\eta$ is an ONet parameterized by $\eta$, $\oplus$ denotes the concatenate operation between codes, $o_p^{(t)}$ is the occupancy of location $p$ in time $t$. Note that the identity code $c_i$ remains the same as it should not change over time.

3.4. Identity Exchange Training

Naively training our network with 4D reconstruction is not sufficient to learn the compositional representation that isolates identity, initial pose, and motion. We introduce a simple yet effective training strategy (shown in Fig. 2), where the network is asked to reconstruct the same motion with different identities. Specifically, we extract latent codes for two sequences, $\{c_{i1}, c_{m1}, c_{p1}\}$ and $\{c_{i2}, c_{m2}, c_{p2}\}$, from different subjects $s_1$ and $s_2$. We then swap their identity codes and supervise the model to reconstruct ground truth 4D captures of the same motion performed by the other subjects, i.e. $s_1$ performing motion of $s_2$ and vice versa. Since the $c_{m1}$ and $c_{p1}$ has no visibility to $s_2$, all the identity information for $s_2$ has to be encoded in $c_{i2}$ for successful reconstruction. In practice, we perform this identity exchange training strategy for 50% of the iteration, and find it effective in disentangling identity and motion.
3.5. Loss Functions

Our model is trained by minimizing the binary cross entropy error (BCE) on the occupancy of 3D locations. Inspired by Occupancy Network [33], we randomly sample a time step $\tau$ and a set of 3D query points $S$, and compute the loss $L(\tau)$ between the predicted $\hat{o}(\tau)$ and the ground truth $o(\tau)$ occupancy values:

$$L(\tau) = \sum_{p \in S} \text{BCE} \left( \hat{o}(\tau), o(\tau) \right). \quad (3)$$

To get $S$, we normalize all the meshes to $[-0.5, 0.5]$, and sample 50% points uniformly in a bounding volume and 50% points near the surface of the mesh. We find the definition of the bounding volume affects the training performance, and experiment with two ways: 1) a fixed volume with length of 1; 2) a tight bounding volume around the mesh, in our experiments.

During training, we also supervise the predicted occupancy value at time step 0 to ensure a high quality initialization. Therefore, the complete loss function is defined as:

$$L = \lambda_1 L(0) + \lambda_2 L(\tau), \quad (4)$$

where $\lambda_1 = \lambda_2 = 1.0$ in all the experiments. We use Adam optimizer with the learning rate as $10^{-4}$. The model is trained with batch size equalling to 16 on a single Tesla V100 GPU.

4. Experiments

In this section, we perform extensive experiments evaluate our method. We first show the ability for 4D reconstruction, and then apply our compositional representation for various tasks like motion transfer and 4D completion.

4.1. Data Preparation

We use two datasets to train and evaluate our proposed method. The first dataset is Dynamic FAUST (D-FAUST) [6], which contains 129 mesh sequences of 10 real human subjects performing 14 different motions and all meshes are registered with SMPL [28] model. We augment D-FAUST to meet the needs of our Identity Exchanging Training strategy (Sec. 3.4). We first fit SMPL shape and pose parameters for all the data. Then, the ground truth mesh sequences of all the combinations of identities and motions are generated, extending the total number of mesh sequences to about 1000.

We also build a Warping Cars dataset using the approach introduced in Occupancy Flow [37] to investigate the performance of our method on non-human objects. Specifically, we randomly choose 10 car models from ShapeNet [9] Car category and generate 1000 warplings. To generate a warping field, Gaussian displacement vectors are sampled in a $3 \times 3 \times 3 \times 5$ grid and the RBF [39] interpolation is used to obtain a continuous displacement field. We combine different car shapes and warplings and finally get the dataset with total number of mesh sequences to 10000, each of which has 50 time steps.

4.2. 4D Reconstruction

We first verify the reconstruction ability of our model following the setting in Occupancy Flow [37]. The network consumes 300 sparse point trajectories as input, each of which consists 3D locations at $L = 17$ equally divided time stamps, and the goal is to reconstruct compact mesh at these time stamps even though the model is able to produce mesh at any particular time. For human model, we use the same train/test split on D-FAUST [6] as Occupancy Flow (OFlow), including data on subjects seen and unseen during the training respectively. For warping car dataset, we test on our own test set as it was not released.

The quantitative results on the D-FAUST dataset and the Warping Cars dataset are summarized in Tab. 1, where we report the average IoU and Chamfer Distance over 17 frames of all testing sequences. As our baseline, “PSGN 4D” is a 4D extension of Point Set Generation Network by predicting a set of trajectories instead of single points, and “ONet 4D” is an extension of Occupancy Network (ONet), which predicts occupancy value for points sampled in 4D space and reconstructs each frame of the sequence separately. OFlow uses Neural ODE to learn a continuous motion vector field for every point in space and time. While OFlow explicitly transform the 3D coordinates of each point, we transform the pose code in the latent space. The results of baselines on the D-FAUST dataset are cited from OFlow [37], and the results on Warping Cars dataset is produced by a retrained OFlow. Overall, our method performs comparable or better than other methods on D-FAUST Warping Cars dataset, indicating that our model is able to reconstruct accurate surfaces.

In Fig. 3, we show qualitative comparison on the D-FAUST dataset with OFlow. Our method is able to capture more details, such as the shape of the opening hands and the outline of the muscles on the body. In particular, OFlow fails to track the motion of hands in the last frame of the left sequence, while our method produces stable results during the whole sequence time. This is presumably because our method reconstructs each frame of the whole sequence individually with the transformed pose latent code, while OFlow only reconstructs the first frame and deforms it with the learned transformation flow. Furthermore, the qualitative results on the Warping Cars dataset are shown in Fig. 4, in which our methods shows better capability of recovering motion than OFlow.
4.3. Pose and Motion Transfer

Our compositional representation also naturally support motion transfer. Consider two subjects performing different motions, namely \(id_1 + \text{motion}_1\) and \(id_2 + \text{motion}_2\), and our goal is to generate 4D sequence with \(id_2 + \text{motion}_1\). To do so, we first extract the latent representations with our compositional encoder for each input sequence, namely namely \((c_i^1, c_{po}^1, c_m^1)\), \((c_i^2, c_{po}^2, c_m^2)\), and then feed \((c_i^2, c_{po}^1, c_m^1)\) to the latent pose transformer and implicit occupancy decoder.

We evaluate our method on D-FAUST test set, where we randomly select 20 identity and motion pairs, and generate the ground truth 4D sequences after motion transfer using the known SMPL parameters. As baseline, we compare to OFlow which also learns separate codes to represent first frame geometry (i.e. the identity) and velocity field (i.e. the motion) respectively. In addition, we also build a baseline with recent state-of-the-art neural pose transfer method NPT [55], which utilizes spatially adaptive instance normal-
ization to deform the identity point cloud to each time step of the target motion sequence using pose transfer. The transformed point clouds are then fed into OFlow to generate complete mesh.

The quantitative results are shown in Tab. 2. Our method significantly outperforms other baseline methods with large margins. One qualitative comparison is shown in Fig. 5. The performance of NPT is heavily limited by the density of the input identity and motion sequences, which makes it hard to transfer the continuous motion with sparse inputs. OFlow does not transfer the motion at all, presumably because the pose representations are not decoupled from the shape latent code, which leads to a wrong first frame pose initialization and the failure of the whole generated sequence. In contrast, our method successfully transfer the motion to the new identity, including both the initial pose and following frames. Additional results on Warping Car dataset are shown in Supplementary Materials.

| Method | IoU | Chamfer Distance |
|--------|-----|------------------|
| NPT    | 26.4% | 0.498            |
| OFlow  | 26.7% | 0.400            |
| Ours   | 85.0% | 0.055            |

Table 2: Motion transfer on D-FAUST testing set.

We further investigate if the motion code $c_m$ can be transferred without initial pose code $c_p$. Even though this is sometimes ill-posed problem (e.g. forcing a stand-up motion to start with a standing pose), we find, surprisingly, our model is still able to produce reasonable results if the new initial pose is not too different from the original one (See Supplementary Material for results). This indicates that our conditional Neural ODE is robust to some extent against the noise in the initial pose code.

| Methods | Temporal IoU | Temporal CD | Spatial IoU | Spatial CD |
|---------|--------------|-------------|-------------|------------|
| OFlow   | 85.2%        | 0.056       | 86.0%       | 0.054      |
| Ours    | 86.3%        | 0.056       | 87.2%       | 0.051      |

Table 3: 4D temporal completion and spatial completion (D-FAUST). CD is short for Chamfer Distance.

4.4. 4D Completion

Our compositional 4D representation also provides strong prior as the regularization for 4D completion task, in which the goal is to fill in the missing signals in a given 4D capture with only partial observation. This is practically useful when part of the 4D capture is corrupted due to imperfect capturing techniques or challenging scenarios. Specifically, this task can be categorized into two kinds based the missing data: 1) Temporal completion, which recovers the missing frames; 2) Spatial completion, which
complete partial geometry in each frame. To perform these task, we remove the encoder, fix the decoder parameters, and optimize the latent codes with back-propagation until the output 4D sequences matches the partial observation.

The experiments are conducted on the D-FAUST dataset. For temporal completion, we select 18 mesh sequences with \( L = 30 \) frames from the testing set, and randomly withhold half of the frames in each sequence for testing. For spatial completion, we randomly select three points in each frame and remove the points less than 0.2 away from them.

Comparison to OFlow is shown in Tab. 3. Our method performs comparable or better IoU and Chamfer distance than OFlow on both temporal and spatial completion. Fig. 6 shows a temporal completion results. Our method successfully interpolate correct poses for missing temporal frames with more complete geometry than OFlow. Please refer to Supplementary Materials for results on Warping Car dataset.

4.5. Future Prediction

Not only interpolating internal missing frames, our model can also predict the future of the motion by extrapolating temporal frames onward. To validate this, we select 15 mesh sequences with \( L = 20 \) frames from the testing set, and always remove the last 10 frames instead of randomly selected ones. Tab. 4 and Fig. 7 shows the comparison to OFlow. Though OFlow can also produce reasonable future motion, the magnitudes are usually small which leads to overly slow motion. In contrast, our method predicts much more accurate motion, e.g. with the other leg raised.

| Methods | D-FAUST IoU | CD | Warping Cars IoU | CD |
|---------|-------------|----|------------------|----|
| OFlow  | 82.6%       | 0.070 | 70.2%           | 0.206 |
| Ours   | 85.9%       | 0.060 | 76.1%           | 0.152 |

Table 4: Future prediction. We remove the last 10 frames of the test sequence to investigate the extrapolation ability of our method.

5. Conclusion

This paper introduces a compositional representation for 4D captures by disentangling the geometry template, initial state and temporal deformation with separated compact latent codes, which can reconstruct the deforming 3D object over a temporal span. Furthermore, an identity exchange training strategy is proposed to make geometry template and temporal deformation efficiently decoupled and exchangeable. Extensive experiments on 4D reconstruction, pose and motion transfer, 4D completion, and motion prediction validate the efficacy of our proposed approach.
References

[1] Panos Achlioptas, Olga Diamanti, Ioannis Mitliagkas, and Leonidas Guibas. Representation learning and adversarial generation of 3d point clouds. arXiv preprint arXiv:1707.02392, 2(3):4, 2017. 1, 2
[2] Thiemo Alldieck, Marcus Magnor, Weipeng Xu, Christian Theobalt, and Gerard Pons-Moll. Video based reconstruction of 3d people models. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 8387–8397, 2018. 2
[3] Nina Amenta, Marshall Bern, and Manolis Kamvysselis. A new voronoi-based surface reconstruction algorithm. In Proceedings of the 25th annual conference on Computer graphics and interactive techniques, pages 415–421, 1998. 2
[4] Aseem Behl, Omid Hosseini Jafari, Siva Karthik Mustikovela, Hassan Abu Alhaija, Carsten Rother, and Andreas Geiger. Bounding boxes, segmentations and object coordinates: How important is recognition for 3d scene flow estimation in autonomous driving scenarios? In Proceedings of the IEEE International Conference on Computer Vision, pages 2574–2583, 2017. 2
[5] Volker Blanz and Thomas Vetter. A morphable model for the synthesis of 3d faces. In Proceedings of the 26th annual conference on Computer graphics and interactive techniques, pages 187–194, 1999. 2
[6] Federica Bogo, Javier Romero, Gerard Pons-Moll, and Michael J Black. Dynamic faust: Registering human bodies in motion. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 6233–6242, 2017. 5
[7] Jean-Daniel Boissonnat. Geometric structures for three-dimensional shape representation. ACM Transactions on Graphics (TOG), 3(4):266–286, 1984. 2
[8] Rohan Chabra, Jan Eric Lenssen, Eddy Ilg, Tanner Schmidt, Julian Straub, Steven Lovegrove, and Richard Newcombe. Deep local shapes: Learning local sdf priors for detailed 3d reconstruction. In Proceedings of the European Conference on Computer Vision (ECCV), 2020. 2
[9] Angel X. Chang, Thomas Funkhouser, Leonidas Guibas, Pat Hanrahan, Qixing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, Jianxiong Xiao, Li Yi, and Fisher Yu. ShapeNet: An Information-Rich 3D Model Repository. Technical Report arXiv:1512.03012 [cs.GR], Stanford University — Princeton University — Toyota Technological Institute at Chicago, 2015. 5
[10] Chao Wen, Yinda Zhang, Zhuwen Li, and Yanwei Fu. Pixel2mesh++: Multi-view 3d mesh generation via deformation. In ICCV, 2019. 2
[11] Ricky TQ Chen, Yulia Rubanova, Jesse Bettencourt, and David K Duvenaud. Neural ordinary differential equations. In Advances in neural information processing systems, pages 6571–6583, 2018. 1, 2, 4
[12] Julian Chibane, Thiemo Alldieck, and Gerard Pons-Moll. Implicit functions in feature space for 3d shape reconstruction and completion. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6970–6981, 2020. 2
[13] Christopher B Choy, Danfei Xu, JunYoung Gwak, Kevin Chen, and Silvio Savarese. 3d-r2n2: A unified approach for single and multi-view 3d object reconstruction. In ECCV, 2016. 1, 2
[14] Junting Dong, Qing Shuai, Yuanqing Zhang, Xian Liu, Xiaowei Zhou, and Hujun Bao. Motion capture from internet videos. In European Conference on Computer Vision, pages 210–227, Springer, 2020. 2
[15] Philipp Erler, Paul Guerrero, Stefan Oehrhallinger, Niloy J. Mitra, and Michael Wimmer. Points2surf: Learning implicit surfaces from point clouds. In ECCV, 2020. 2
[16] Haoqiang Fan, Hao Su, and Leonidas J Guibas. A point set generation network for 3d object reconstruction from a single image. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 605–613, 2017. 1, 2
[17] Rohit Girdhar, David F. Fouhey, Mikael Rodriguez, and Abhinav Gupta. Learning a predictable and generative vector representation for objects. In ECCV, 2016. 1, 2
[18] Thibault Groueix, Matthew Fisher, Vladimir G Kim, Bryan C Russell, and Mathieu Aubry. Atlasnet: A paper-mâché approach to learning 3d surface generation. arXiv preprint arXiv:1802.05384, 2018. 1, 2
[19] Jiawei He, Andreas Lehrmann, Joseph Marino, Greg Mori, and Leonid Sigal. Probabilistic video generation using holistic attribute control. In Proceedings of the European Conference on Computer Vision (ECCV), pages 452–467, 2018. 2
[20] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016. 4
[21] Xun Huang and Serge Belongie. Arbitrary style transfer in real-time with adaptive instance normalization. In Proceedings of the IEEE International Conference on Computer Vision, pages 1501–1510, 2017. 3
[22] Chiyu Jiang, Avneesh Sud, Ameesh Makadia, Jingwei Huang, Matthias Nießner, and Thomas Funkhouser. Local implicit grid representations for 3d scenes. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6001–6010, 2020. 1, 2
[23] Angjoo Kanazawa, Shubham Tulsiani, Alexei A Efros, and Jitendra Malik. Learning category-specific mesh reconstruction from image collections. In Proceedings of the European Conference on Computer Vision (ECCV), pages 371–386, 2018. 1, 2
[24] Angjoo Kanazawa, Jason Y Zhang, Panna Felsen, and Jitendra Malik. Learning 3d human dynamics from video. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5614–5623, 2019. 2
[25] Hiroharu Kato, Yoshitaka Ushiku, and Tatsuya Harada. Neural 3d mesh renderer. In CVPR, 2018. 2
[26] Michael Kazhdan, Matthew Bolitho, and Hugues Hoppe. Poisson surface reconstruction. In Proceedings of the fourth Eurographics symposium on Geometry processing, volume 7, 2006. 2
[27] Yiyi Liao, Simon Donne, and Andreas Geiger. Deep marching cubes: Learning explicit surface representations. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2916–2925, 2018. 2
[28] Matthew Loper, Naureen Mahmood, Javier Romero, Gerard Pons-Moll, and Michael J Black. Smpl: A skinned multi-person linear model. ACM transactions on graphics (TOG), 34(6):1–16, 2015. 2, 5

[29] William E. Lorensen and Harvey E. Cline. Marching cubes: A high resolution 3d surface construction algorithm. In SIGGRAPH, 1987. 2

[30] William E Lorensen and Harvey E Cline. Marching cubes: A high resolution 3d surface construction algorithm. ACM siggraph computer graphics, 21(4):163–169, 1987. 4

[31] Dushyant Mehta, Oleksandr Sotnychenko, Franziska Mueller, Weipeng Xu, Mohamed Elgharib, Pascal Fua, Hans-Peter Seidel, Helge Rhodin, Gerard Pons-Moll, and Christian Theobalt. Xnect: Real-time multi-person 3d motion capture with a single rgb camera. ACM Transactions on Graphics (TOG), 39(4):82–1, 2020. 2

[32] Moritz Menze and Andreas Geiger. Object scene flow for autonomous vehicles. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3061–3070, 2015. 2

[33] Lars Mescheder, Michael Oechsle, Michael Niemeyer, Sebastian Nowozin, and Andreas Geiger. Occupancy networks: Learning 3d reconstruction in function space. In Proceedings IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), 2019. 1, 2, 4, 5

[34] Ishan Misra, Abhinav Gupta, and Martial Hebert. From red wine to red tomato: Composition with context. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1792–1801, 2017. 3

[35] Armin Mustafa, Hansung Kim, Jean-Yves Guillemaut, and Adrian Hilton. General dynamic scene reconstruction from multiple view video. In Proceedings of the IEEE International Conference on Computer Vision, pages 900–908, 2015. 2

[36] Jan Neumann and Yiannis Aloimonos. Spatio-temporal stereo using multi-resolution subdivision surfaces. International Journal of Computer Vision, 47(1-3):181–193, 2002. 2

[37] Michael Niemeyer, Lars Mescheder, Michael Oechsle, and Andreas Geiger. Occupancy flow: 4d reconstruction by learning particle dynamics. In Proceedings of the IEEE International Conference on Computer Vision, pages 5379–5389, 2019. 1, 2, 3, 4, 5

[38] Chengjie Niu, Jun Li, and Kai Xu. Im2struct: Recovering 3d shape structure from a single rgb image. In CVPR, 2018. 2

[39] Jooyoung Park and Irwin W Sandberg. Universal approximation using radial-basis-function networks. Neural computation, 3(2):246–257, 1991. 5

[40] Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, and Steven Lovegrove. Deepsdf: Learning continuous signed distance functions for shape representation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 165–174, 2019. 1, 2, 4

[41] Taesung Park, Jun-Yan Zhu, Oliver Wang, Jingwu Lu, Eli Shechtman, Alexei A Efros, and Richard Zhang. Swapping autoencoder for deep image manipulation. arXiv preprint arXiv:2007.00653, 2020. 3

[42] Yuri Pekelny and Craig Gotsman. Articulated object reconstruction and markerless motion capture from depth video. In Computer Graphics Forum, volume 27, pages 399–408. Wiley Online Library, 2008. 2

[43] Leonid Pishchulin, Stefanie Wuhrer, Thomas Helten, Christian Theobalt, and Bernt Schiele. Building statistical shape spaces for 3d human modeling. Pattern Recognition, 67:276–286, 2017. 2

[44] Lev Semenovich Pontryagin. Mathematical theory of optimal processes. Routledge, 2018. 4

[45] Charles R. Qi, Wei Liu, Chenxia Wu, Hao Su, and Leonidas J. Guibas. Frustum pointnets for 3d object detection from RGB-D data. In CVPR, 2018. 1, 2

[46] Charles Ruizhongtai Qi, Hao Su, Kaichun Mo, and Leonidas J. Guibas. Pointnet: Deep learning on point sets for 3d classification and segmentation. In CVPR, 2017. 1, 2, 4

[47] Davis Rempe, Tolga Birdal, Yongheng Zhao, Zan Gjojic, Srinath Sridhar, and Leonidas J Guibas. Caspr: Learning canonical spatiotemporal point cloud representations. Advances in Neural Information Processing Systems, 33, 2020.

[48] Austin Stone, Huayan Wang, Michael Stark, Yi Liu, D Scott Phoenix, and Dileep George. Teaching compositionality to cnns. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 5058–5067, 2017. 3

[49] Maxim Tatarchenko, Alexey Dosovitskiy, and Thomas Brox. Octree generating networks: Efficient convolutional architectures for high-resolution 3d outputs. In ICCV, 2017. 2

[50] Ayush Tewari, Florian Bernard, Pablo Garrido, Gaurav Bharaj, Mohamed Elgharib, Hans-Peter Seidel, Patrick Pérez, Michael Zollhofer, and Christian Theobalt. Fml: Face model learning from videos. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10812–10822, 2019. 3

[51] Pavel Tokmakov, Yu-Xiong Wang, and Martial Hebert. Learning compositional representations for few-shot recognition. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 6372–6381, 2019. 3

[52] Ali Osman Ulusoy, Octavian Biris, and Joseph L Mundy. Dynamic probabilistic volumetric models. In Proceedings of the IEEE International Conference on Computer Vision, pages 505–512, 2013. 2

[53] Ali Osman Ulusoy and Joseph L Mundy. Image-based 4-d reconstruction using 3-d change detection. In European Conference on Computer Vision, pages 31–45. Springer, 2014. 2

[54] Michael Wand, Philipp Jenke, Qixing Huang, Martin Bauer, Philipp Müller, Weipeng Xu, Mohamed Elgharib, Hans-Peter Seidel, Patrick Pérez, and Christian Theobalt. Fml: Face model learning from videos. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10812–10822, 2019. 3

[55] Jiashun Wang, Chao Wen, Yanwei Fu, Haitao Lin, Tianyun Zou, Xiangyang Xue, and Yinda Zhang. Neural pose transfer by spatially adaptive instance normalization. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5831–5839, 2020. 3, 6
[56] Kangkan Wang, Jin Xie, Guofeng Zhang, Lei Liu, and Jian Yang. Sequential 3d human pose and shape estimation from point clouds. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7275–7284, 2020. 2

[57] Nanyang Wang, Yinda Zhang, Zhuwen Li, Yanwei Fu, Wei Liu, and Yu-Gang Jiang. Pixel2mesh: Generating 3d mesh models from single rgb images. In ECCV, 2018. 1, 2

[58] Peng-Shuai Wang, Yang Liu, Yu-Xiao Guo, Chun-Yu Sun, and Xin Tong. O-cnn: Octree-based convolutional neural networks for 3d shape analysis. ACM Transactions on Graphics (TOG), 36(4):72, 2017. 1, 2

[59] Qiangeng Xu, Weiyue Wang, Duygu Ceylan, Radomir Mech, and Ulrich Neumann. Disn: Deep implicit surface network for high-quality single-view 3d reconstruction. arXiv preprint arXiv:1905.10711, 2019. 4

[60] Qian Zheng, Xiaochen Fan, Minglun Gong, Andrei Sharf, Oliver Deussen, and Hui Huang. 4d reconstruction of blooming flowers. In Computer Graphics Forum, volume 36, pages 405–417. Wiley Online Library, 2017. 2

[61] Jun-Yan Zhu, Zhoutong Zhang, Chengkai Zhang, Jiajun Wu, Antonio Torralba, Josh Tenenbaum, and Bill Freeman. Visual object networks: Image generation with disentangled 3d representations. In Advances in neural information processing systems, pages 118–129, 2018. 3