Mesh-based Autoencoders for Localized Deformation Component Analysis

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Abstract
Spatially localized deformation components are very useful for shape analysis and synthesis in 3D geometry processing. Several methods have recently been developed, with an aim to extract intuitive and interpretable deformation components. However, these techniques suffer from fundamental limitations especially for meshes with noise or large-scale deformations, and may not always be able to identify important deformation components. In this paper we propose a novel mesh-based autoencoder architecture that is able to cope with meshes with irregular topology. We introduce sparse regularization in this framework, which along with convolutional operations, helps localize deformations. Our framework is capable of extracting localized deformation components from mesh data sets with large-scale deformations and is robust to noise. It also provides a nonlinear approach to reconstruction of meshes using the extracted basis, which is more effective than the current linear combination approach. Extensive experiments show that our method outperforms state-of-the-art methods in both qualitative and quantitative evaluations.

1 Introduction
With the development of 3D scanning and modeling technology, mesh data sets are becoming more and more popular. By analyzing these data sets with machine learning techniques, the latent knowledge can be explored to advance geometry processing algorithms. In recent years, many research areas in geometry processing have benefited from this methodology, such as 3D shape deformation (Gao et al. 2016; Wampler 2016), 3D facial and human body reconstruction (Cao et al. 2015; Bogo et al. 2016), shape segmentation (Guo, Zou, and Chen 2015), etc. For shape deformation and human reconstruction, mesh sequences with different geometry and the same connectivity play a central role. Different geometric positions describe the appearance of the 3D mesh model while sharing the same vertex connectivity makes processing much more convenient. In such works, a key procedure is to build a low-dimensional control parametrization for the mesh data set, which provides a small set of intuitive parameters to control the generation of new shapes. For articulated models such as human bodies, the rigging method embeds a skeleton structure in the mesh to provide such a parametrization. However, the rigging operation is restrictive and does not generalize to other deformable shapes (e.g. faces). Parameterizing general mesh datasets which allows intuitive control in generating new shapes becomes an important and urgent research problem.

Early work extracted principal deformation components by using Principal Component Analysis (PCA) to reduce the dimensionality of the data set. However, such deformation components are global which do not lead to intuitive control. For example, when a user intends to deform the shape locally, by specifying locally changed vertex positions as boundary conditions, the deformed shape tends to have unrelated areas deformed as well, due to the global nature of the basis. To address this, sparse localized deformation component (SPLOCS) extraction methods were recently proposed (Neumann et al. 2013; Huang et al. 2014; Wang et al. 2016). In these works the sparsity term is involved to localize deformation components within local support regions. However, these previous works suffer from different limitations: as we will show later, (Neumann et al. 2013; Huang et al. 2014) cannot handle large-scale deformations, and (Wang et al. 2016) is sensitive to noise which cannot extract the main deformation components robustly. We propose a novel mesh-based autoencoder architecture to extract meaningful local deformation components. We represent deformations of shapes in the dataset based on a recent effective representation (Gao et al. 2017) which is able to cope with large deformations. We then build a CNN-based autoencoder to transform the deformation representation to encoding in a latent space. Each convolutional layer involves convolutional operations defined on the mesh with arbitrary topology in the form of applying the same local filter to each vertex and its 1-ring neighbors, similar to (Duvenaud et al. 2015). We then introduce sparsity regularization to the weights in the fully-connected layers to promote identifying sparse localized deformations. The autoencoder structure ensures that the extracted deformation components are suitable for reconstructing high quality shape deformations.

Our main contributions are: 1) This is the first work that exploits CNN-based autoencoders for processing meshes with irregular connectivity. 2) Benefiting from sparse regularization and the nonlinear representation capability of autoencoders, our method is able to extract intuitive localized deformation components. It is able to deal with datasets with large-scale deformations, and is insensitive to noise. The method can extract important components even for chal-
lenging cases and generalize well to reconstruction of unseen data. Extensive qualitative and quantitative experiments demonstrate that our method outperforms the state-of-the-art methods. We show an example of extracted deformation components (highlighted in blue) in Fig. 1, which are then combined to synthesize a novel, plausible shape. The overall architecture of our proposed network is illustrated in Fig. 2.

In the following, we review related work in Sec. 2. In Sec. 3, we describe the features used in this work to make it more self-contained. The architecture of the neural network is described in Sec. 4. Two applications are presented in Sec. 5. The results and evaluations are given in Sec. 6, and finally conclusions are drawn in Sec. 7.

2 Related Work

Principal Deformation Components Analysis. With the increasing availability of 3D shapes, analyzing shape collections is becoming more important. Early work employs PCA to compress the mesh data set and extract global deformation components (Alexa and Muller 2000). The deformation components from the PCA are globally supported, which is not intuitive for shape editing and deformation, especially when the user wants to deform the shape locally in the spatial domain (Havaldar 2006). Sparse regularization is effective in localizing deformations (Gao, Zhang, and Lai 2012). However, standard sparse PCA (Zou, Hastie, and Tibshirani 2004) does not work for shapes since it does not take spatial constraints into account and therefore the extracted deformation components do not aggregate in local spatial domains. By incorporating spatial constraints, a sparsity term is employed to extract spatially localized deformation components (Neumann et al. 2013; Bernard et al. 2016). As shown in (Neumann et al. 2013), this performs better than region-based PCA variants (clustered PCA) (Tena, De la Torre, and Matthews 2011) in terms of extracting meaningful localized deformation components. However, it uses Euclidean coordinates which cannot represent shapes with large rotations. Later work addresses this limitation by using more advanced shape representations including deformation gradients (Huang et al. 2014) and edge and dihedral angle representations (Wang et al. 2016). However, the former cannot cope with rotations larger than 180° which are very common in the animated mesh sequences, while the latter is not sensitive to the scale of the deformation which makes (Wang et al. 2016) not robust to noise. Unlike existing methods, we propose to exploit mesh-based autoencoders with sparse regularization along with an effective deformation representation (Gao et al. 2017) to extract high-quality deformation components, outperforming existing methods.

Neural Network Applications for 3D Shapes. Neural networks have achieved great success in different areas of computer science. Compared with 2D images, 3D shapes are more difficult to process, mainly due to their irregular connectivity and limited data availability. Nevertheless, some effort was made in recent years. For 3D object recognition, Su et al. (2015) and Shi et al. (2015) represent 3D shapes using multi-view projections or converting them to panoramic views and utilize 2D CNNs. Maturana and Scherer (2015) treat 3D shapes as voxels and extend 2D-CNNs to 3D-CNNs to recognize 3D objects. In addition, Li et al. (2015) analyze a joint embedding space of 2D images and 3D shapes. Tulsiani et al. (2016) abstract complex shapes using 3D volumetric primitives. For 3D shape synthesis, Wu et al. (2015) use deep belief networks to generate voxelized 3D shapes. Girdhar et al. (2016) combine an encoder for 2D images and a decoder for 3D models to reconstruct 3D shapes from 2D input. Yan et al. (2016) generate 3D models from 2D images by adding a projection layer from 3D to 2D. Choy et al. (2016) propose a novel recurrent network to map images of objects to 3D shapes. Sharma et al. (2016) train a volumetric autoencoder using noisy data with no labels for tasks such as denoising and completion. Wu et al. (2016) exploit the power of the generative adversarial network with a voxel CNN. In addition to voxel representation, Sinha et al. (2017) propose to combine ResNet and geometry images to synthesis 3D models. Li et al. (2017) and Nash and Williams (2017) propose to use neural networks for encoding and synthesizing 3D shapes based on pre-segmented data. Fan et al. (2016) predict 3D point clouds from images. All the methods above for synthesizing 3D models are restricted by their representations or primitives adopted, which are not suitable for analyzing and generating 3D motion sequences with rich details.

Convolutional Neural Networks on Arbitrary Graphs and Meshes. Traditional convolutional neural networks

Figure 1: Synthesized model by combining deformation components derived from the Swing dataset (2008) by our method with equal weights.

Figure 2: The proposed network architecture.
are defined on 2D images or 3D voxels with regular grids. Researches have explored the potential to extend CNNs to irregular graphs by construction in the spectral domain (Bruna et al. 2013; Henaff, Bruna, and LeCun 2015; Defferrard, Bresson, and Vandergheynst 2016) or the spatial domain (Niepert, Ahmed, and Kutzkov 2016; Duvenaud et al. 2015) focusing on spatial construction. Such representations are exploited in recent work (Boscaini et al. 2016b; 2016a; Yi et al. 2017) for finding correspondences or performing part-based segmentation on 3D shapes. Our method is based on spatial construction and utilize this to build an autoencoder for analyzing deformation components.

3 Feature Representation

To represent large-scale deformations, we adapt a recently proposed deformation representation (Gao et al. 2017). Given a dataset with N shapes with the same topology, each shape is denoted as \( S_m, m \in \{1, \ldots, N\} \), \( m, i \in \mathbb{R}^3 \) is the \( i^{th} \) vertex on the \( m^{th} \) mesh model. The deformation gradient \( T_{m,i} \in \mathbb{R}^{3 \times 3} \) representing local shape deformations can be obtained by minimizing:

\[
\arg\min_{T_{m,i}} \sum_{j \in N(i)} c_{ij} \left\| (p_{m,i} - p_{m,j}) - T_{m,i} (p_{1,i} - p_{1,j}) \right\|^2,
\]

where \( c_{ij} \) is the cotangent weight and \( N(i) \) is the index set of 1-ring neighbors of the \( i^{th} \) vertex. By polar decomposition \( T_{m,i} = R_{m,i} S_{m,i} \), the affine matrix \( T_{m,i} \in \mathbb{R}^{3 \times 3} \) can be decomposed into an orthogonal matrix \( R_{m,i} \) describing rotations, and a real symmetry matrix \( S_{m,i} \) the scale and shear deformations. The rotation matrix \( R_{m,i} \) can be equivalently written as rotating around an axis \( \omega_{m,i} \) by an angle \( \theta_{m,i} \). However, the mapping from the axis-angle representation to rigid rotation is surjective but not one to one: The rotation angles and axes in the set \( \Omega_{m,i} \) correspond to one rigid rotation:

\[
\Omega_{m,i} = \{ (\omega_{m,i}, \theta_{m,i} + t \cdot 2\pi), (\omega_{m,i}, -\theta_{m,i} + t \cdot 2\pi) \}
\]

where \( t \) is an arbitrary integer. To overcome this, (Gao et al. 2017) proposes a novel representation to select the unique and consistent axis-angle representation by solving a global optimization to minimize the differences between adjacent rotation axes and angles.

For each vertex \( i \) of shape \( m \), we obtain feature \( q_{m,i} = \{ r_{m,i}, s_{m,i} \} \in \mathbb{R}^d \) by extracting from matrices \( R_{m,i} \) and \( S_{m,i} \). To fit the scale of output activation function \( tanh \) (explained later), we need to scale the feature values. Denote by \( r_{j,m,i} \) and \( s_{j,m,i} \) the \( j^{th} \) dimension of \( r_{m,i} \) and \( s_{m,i} \) respectively. Separately for each dimension \( j \), we linearly scale \( r_{j,m,i} \) and \( s_{j,m,i} \) from \( [r_{min}, r_{max}] \) and \( [s_{min}, s_{max}] \) to \([−0.95, 0.95]\) to acquire preprocessed \( r_{j,m,i}^\prime \) and \( s_{j,m,i}^\prime \), where \( r_{min} = \min_{m,i,j} r_{j,m,i} \), \( r_{max} \), \( s_{min}, s_{max} \) are defined similarly. Then, we have \( X_{m,i} = \{ r_{m,i}^\prime, s_{m,i}^\prime \} \) as the deformation feature for vertex \( i \) of shape \( m \).

4 Network Architecture

In this section, we present our framework including convolutional operations on irregular meshes, overall network structure, sparsity constraints and reconstruction loss.

**Convolutional Operation**

Our convolutional operation is extended from the work (Duvenaud et al. 2015) originally used for chemical molecules as a graph. In our representation, a mesh with irregular connectivity is the domain, and data vectors are associated with each vertex. For a convolutional layer, it takes input data \( x \in \mathbb{R}^{V \times d} \), where \( V \) is the number of vertices, and \( d \) is the dimension of input data, and produces output data \( y \in \mathbb{R}^{V \times d'} \) where \( d' \) is the dimension of the output data. Denote by \( x_i \) the \( i^{th} \) row of \( x \) corresponding to vertex \( i \). Let its 1-ring neighbor vertices be \( n_{ij} \), \( j = 1, 2, \ldots, D_i \) and \( D_i \) is the degree of vertex \( i \). The convolutional operation is computed as:

\[
y_i = W_{point} x_i + W_{neighbour} \sum_{j=1}^{D_i} x_{n_{ij}} \frac{D_i}{D_i} + b, \tag{1}
\]

where \( W_{point}, W_{neighbour} \in \mathbb{R}^{d' \times d} \) are weights for the convolutional operation, and \( b \in \mathbb{R}^{d'} \) is the bias of the layer.
Ground Truth  | Neumann et al.  | Bernard et al.  
---|---|---
Huang et al.  | Wang et al.  | Ours

Figure 4: Visual comparison of reconstruction results of the SCAPE dataset (2005).

Neumann et al.  | Ours
---|---

Figure 5: Components of horse dataset (2004) extracted by (Neumann et al. 2013) and our method.

Network Structure
The overall network is built based on the convolutional operation, and with an autoencoder structure. The input to the encoder part is preprocessed features which are shaped as $X \in \mathbb{R}^{V \times 9}$, where $9$ is the dimension of the deformation representation. Then we stack several convolutional layers with ReLU as the output activation function. We tested alternative functions like $tanh$, but they performed worse in the quantitative analysis. The number of layers and the dimension of each layer are dependent on the quantitative analysis. The number of layers and the dimension of each layer are dependent on the quantitative analysis.

Encoder Part
The input to the encoder part is preprocessed features which are shaped as $X \in \mathbb{R}^{V \times 9}$, where $9$ is the dimension of the deformation representation. Then we stack several convolutional layers with ReLU as the output activation function. We tested alternative functions like ReLU, but they performed worse in the quantitative analysis. The number of layers and the dimension of each layer are dependent on the quantitative analysis.

Decoder Part
For the decoder convolutional layers, we use the transpose of the corresponding layer in the encoder, with all parameters based on normalized geodesic distances:

$$z = Cf,$$

where $C_i$ is the $i$-th column of $C$.

$$f = C^Tz,$$

Sparsity Constraints and Reconstruction Loss
Following the idea from (Neumann et al. 2013), we use group sparsity ($L_{2,1}$ norm) to urge deformation components to only capture local deformations. The constraints are added on $C$ as:

$$\Omega(C) = \frac{1}{K} \sum_{k=1}^{K} \sum_{i=1}^{V} \lambda_{ik} \|C_i^T C_k\|_2,$$

where $C_k^T$ is the $k$-th dimensional vector associated with component $k$ of vertex $i$, and $\lambda_{ik}$ is sparsity regularization parameter based on normalized geodesic distances:

$$\lambda_{ik} = \begin{cases} 0 & d_{ik} < d_{\min} \\ 1 & d_{\min} \leq d_{ik} \leq d_{\max} \\ \frac{d_{\max} - d_{\min}}{d_{\max} - d_{\min}} & \text{otherwise.} \end{cases}$$

$$d_{ik}$$ denotes the normalized geodesic distance from vertex $i$ to the center point $c_k$ of component $k$ which is defined as:

$$c_k = \arg\max_i \|C_k^T\|_2.$$

$C_k$ will be updated after optimizing $C$ in each iteration. Intuitively, $\Lambda$ maps a geodesic distance to the range of $[0, 1]$ with distances out of the range of $[d_{\min}, d_{\max}]$ capped. $d_{\min}$ and $d_{\max}$ are user-defined.

| Dataset  | Metric       | Method       | Neumann et al. | Bernard et al. |
|----------|--------------|--------------|----------------|----------------|
|          | $E_{rms}$    | Ours         | Wang et al.    | Huang et al.   |
| Horse    | $12.9605$    | $29.6090$    | $18.0624$      | $\textbf{7.3682}$ |
|          | $0.04004$    | $0.04332$    | $0.05273$      | $0.08074$      | $0.4111$ |
| Face     | $2.9083$     | $8.5620$     | $12.3221$      | $2.9106$       | $2.9853$ |
|          | $0.007344$   | $0.01320$    | $0.01827$      | $0.008611$     | $0.02662$ |
| ‘Jumping’| $24.4827$    | $44.3362$    | $37.9915$      | $29.3368$      | $49.9374$ |
|          | $0.04862$    | $0.05400$    | $0.06305$      | $0.1268$       | $0.4308$ |
| Humanoid | $3.4912$     | $60.9925$    | $16.1995$      | $14.3610$      | $6.6320$ |
|          | $0.01313$    | $0.03757$    | $0.02247$      | $0.07319$      | $0.04612$ |
\(d_{\text{max}}\) are two tunable parameters, and control the size of deformation region of one component. For most datasets, we use \(d_{\text{min}} = 0.2\) and \(d_{\text{max}} = 0.4\). To fit the training process of neural network, we precomputed all the geodesic distances between two vertices using (Crane, Weischedel, and Wardetzky 2013), which are then normalized by dividing them by the largest geodesic distance among two possible vertex pairs.

Since \(C^T Z = (C^T X)(\alpha Z)\ \forall \alpha \neq 0\), to avoid trivial solutions with arbitrarily small \(C\) values and arbitrary large \(Z\) values, we also add constraints to \(Z\) as a regularization term:

\[
\mathcal{V}(Z) = \frac{1}{K} \sum_{j=1}^{K} (\max_m |Z_{jm}| - \theta),
\]

where \(Z_{jm}\) is the \(j\)th dimension of model \(m\)’s weight, and \(\theta\) is a small positive number. We set \(\theta = 5\) in all the experiments. We use Mean Square Error (MSE) to urge the network to reconstruct the representation of models, and the total loss function is:

\[
\mathcal{L} = \frac{1}{N} \sum_{m=1}^{N} \|\hat{X}_m - X_m\|^2 + \lambda_1 \Omega(C) + \lambda_2 \mathcal{V}(Z),
\]

where \(\hat{X}_m\) and \(X_m\) are input and output of model \(m\) (data term), \(\Omega(C)\) is the sparse localized regularization. We set \(\lambda_1 = \lambda_2 = 0.5\) in all the experiments. The whole network pipeline is illustrated in Fig. 2. We use ADAM algorithm (Kingma and Ba 2015) and set the learning rate to be 0.001 to train the network.

5 Applications

Once trained, the network can be used to perform many useful tasks, including dimensionality reduction, reconstruction, component analysis and shape synthesis. The first two applications are straightforward, so we now give details for performing the last two applications.

Component Analysis

The matrix \(C\) corresponds to the localized deformation components. We assume the \(r\)th model is the reference model (which can be the first model in the dataset) which has a latent vector \(Z_r\). To analyze the \(r\)th deformation component, we calculate the minimum and maximum values of the \(i\)th dimension of the embedding, denoted by \(Z_{i, \text{min}} = \min_m Z_{i,m}\) and \(Z_{i, \text{max}} = \max_m Z_{i,m}\). We can then obtain latent vectors \(\hat{Z}_{i, \text{min}}\) and \(\hat{Z}_{i, \text{max}}\) corresponding to the two extreme values of the \(r\)th component by replacing the \(r\)th component of \(Z_r\) with \(Z_{i, \text{min}}\) and \(Z_{i, \text{max}}\), respectively. Applying the vectors to the decoder produces the output mesh features \(\hat{X}_{i, \text{min}}\) and \(\hat{X}_{i, \text{max}}\). We work out the differences \(\|\hat{X}_{i, \text{min}} - X_r\|\) and \(\|\hat{X}_{i, \text{max}} - X_r\|\) as the lower bound and upper bound of the \(r\)th component for evaluating shape generalization.
Figure 8: Comparison of deformation components located in similar areas, which are extracted by different methods.

\[ \| \hat{x}_{\text{max}} - X_r \| \]

and the one that has larger distance from the reference model \( X_r \) is chosen as the representative shape for the \( i^{th} \) deformation component, with the corresponding latent vector denoted as \( Z_{ir} \). The displacement of each vertex feature indicates the strength of the deformation, which can be visualized to highlight changed positions.

**Shape Synthesis**

To synthesize new models, the user can specify a synthesis weight \( w_i \) for the \( i^{th} \) deformation component, and the deformed shape in the latent space can be obtained as:

\[
z_{si} = Z_{ir} + (Z_{ih} - Z_{ir}) \times w_i,
\]

where \( z_{si} \) represents the \( i^{th} \) dimension of obtained weight \( z_s \) in the latent space. Then, by feeding \( z_s \) as input to the decoder, the synthesized model feature can be obtained which can be used for reconstructing synthesized shape.

6 Experimental Results

**Quantitative Evaluation**

We compare the generalization ability of our method with several state-of-the-art methods, including original SPLOCS (Neumann et al. 2013), SPLOCS with deformation gradients (Huang et al. 2014), SPLOCS with edge lengths and dihedral angles (Wang et al. 2016), SPLOCS with the feature from (Gao et al. 2017) as used in this paper, and method from (Bernard et al. 2016). We use two datasets SCAPE from (Anguelov et al. 2005) and Swing from (Vlasic et al. 2008) to conduct main quantitative evaluation.

For the SCAPE dataset, we randomly choose 36 models as the training set and the remaining 35 models as the test set. After training, we compare the generalization error on the test set with different methods, using \( E_{rms} \) (root mean square) error (Kavan, Sloan, and O’Sullivan 2010). The results are shown in Fig. 3(a). Fig. 4 shows the visual comparison of reconstruction results. For the Swing dataset, we randomly select one model from every ten models and set them as the training set (15 models). The remaining models belong to the test set (135 models). We compare \( E_{rms} \) error and \( STED \) error proposed by (Vasa and Skala 2011) which is designed for motion sequences and focuses on ‘perceptual’ error of models. The results are shown in Figs. 3(b) and 3(c). Note that since the vertex position representation cannot handle rotation well, the more components (Neumann et al. 2013) and (Bernard et al. 2016) use, the more artifacts would be brought in the reconstructed models, thus \( STED \) error may increase when the number of components increase. The results indicate that our method has better quantitative reconstruction results than other methods, with lower reconstruction errors when sufficient components are used. From the visual results, we can see that (Neumann et al. 2013), (Bernard et al. 2016) and (Huang et al. 2014) cannot handle large-scale rotations well and cannot reconstruct plausible models in such cases, while (Wang et al. 2016) can be affected by noise in the dataset and cannot recover some actions precisely. Our method does not have such drawbacks. Comparison with SPLOCS using (Gao et al. 2017) demonstrates that our autoencoder is effective, beyond the benefits from the representation.

From the previous experiment, we can conclude that 50 components are generally sufficient to fit data well for all the
methods. We then compare more results on several datasets using 50 components, and summarize the results in Table 1. All the datasets we use here can be seen as motion sequences, so we use the same training-test split used for the Swing dataset, and use these two metrics to evaluate the error. Although for the Horse dataset (Sumner et al. 2005), the method (Neumann et al. 2013) has a lower $E_{rms}$ error than our method, their method cannot cope with such dataset with large deformations and suffer from artifacts. The components extracted by our method and (Neumann et al. 2013) are shown in Fig. 5.

Meanwhile, to quantitatively compare the sparse control ability of these methods, we randomly select a few points on the mesh and test the ability of each method to recover the whole mesh through these limited points. This situation is similar to the scenario that users put limited control points on significant joints to acquire models with meaningful actions. To get the control points evenly distributing on the mesh surface, we randomly choose the first point, and then use Voronoi sampling to acquire the other points. We test the results on SCAPE and Swing datasets. For both methods, we choose 50 components, and for (Neumann et al. 2013) and (Bernard et al. 2016), we solve the reconstruction problem directly using the limited points, while for the other methods, we use data-driven deformation with the extracted components. We show the results in Fig. 6. The results show that our method perform well in this task, consistently with smallest errors in both metrics. The datasets we use in this experiment contain a great amount of rotation. Therefore, using limited control points may not allow the components extracted by (Neumann et al. 2013) and (Bernard et al. 2016) to recover the whole mesh, resulting in the great fluctuation in the error curves.

Qualitative Evaluation

Flag Dataset. To verify our method’s ability to capture primary deformation components even when there is significant noise, we test on a flag dataset created by physical simulation and compare our method with (Wang et al. 2016). For both methods, we extract 20 components, and the first four components along with the key frames of the dataset are shown in Fig. 7. Our method is able to extract the main movements (large-scale swinging of the flag), and separate local movements in the left and right parts of the flag. The synthesized result with the four components is reasonable. However, (Wang et al. 2016) only captures the noise around the corner of flags, and the reconstructed shape does not capture the true deformation.

SCAPE Dataset. We compare our results on the SCAPE dataset (Anguelov et al. 2005) with SPLOCS (Neumann et al. 2013), SPLOCS with deformation gradients (Huang et al. 2014) and (Bernard et al. 2016). The corresponding components extracted by our method and the other methods are shown in Fig. 8, and two groups of components about lifting the left leg (extracted by our method and Neumann et al.) and left arm (extracted by our method and Huang et al.) with different weights are shown in Fig. 9. These justify that our method can handle large-scale rotation better than the other methods without artifacts like irrational amplification and shrinkage. Our proposed method also has powerful synthesis ability. We show synthesis results by combining several different deformation components in Fig. 10.

Swing and Jumping Datasets. For Swing and Jumping datasets from (Vlasic et al. 2008), we first align all the models and then train the network. The synthesis results of our method are compared with those of (Wang et al. 2016) in Fig. 11. The first group of components are about shaking head to left from the Jumping dataset. Our method focuses on the movement of the head and can produce reasonable models, while models generated by Wang et al. are disturbed by the clothes, and have artifacts of arm structure. The second group of models are about lifting the left arms from the Swing dataset, Wang et al. even finds wrong direction for this movement. We show synthesis results by combining three different deformation components in Fig. 1.

7 Conclusion

In this paper, we propose a novel CNN based autoencoder on meshes to extract localized deformation components. Extensive quantitative and qualitative evaluations show that our method is effective, outperforming state-of-the-art methods.

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