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DEFORMATION TRANSFER OF 3D HUMAN SHAPES AND POSES ON MANIFOLDS

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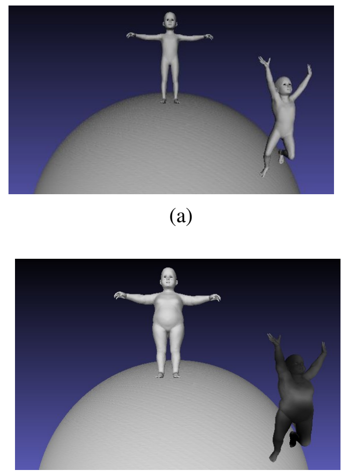
ABSTRACT

In this paper, we introduce a novel method to transfer the deformation of a human body to another directly on a manifold. There exists a rich literature on transferring deformations based on Euclidean representations. However, a 3D human shape and pose live on a manifold and have a Riemannian structure. The proposed method uses the *Lie Bodies* manifold representation of 3D triangulated bodies. Its benefits are preserved, namely, minimum required degrees of freedom for any triangle deformation and no heuristics to constrain excessive ones. We give a closed form solution for deformation transfer directly on the *Lie Bodies*. The deformations have strictly positive determinants ensuring that non-physical deformations are removed. We show examples on three datasets, and highlight differences with the Euclidean deformation transfer.

Index Terms— Deformation transfer, Lie Bodies, shape modeling, pose modeling.



(a)

(b)

Fig. 1: Transfer a target pose from a reference (a) to a new subject (b) given known initial poses in Lie Bodies [10].

1. INTRODUCTION

Deforming meshes is essential for animation and computer modeling applications. Hand-crafting deformations can take a considerable time as it requires special skills and an artistic touch. Moreover, if the created deformation is to be reused for another shape, the deformation parameters need to be adapted to it. This might be as time consuming as the original crafting.

In this work, we focus on shape and pose deformation transfer from a 3D human body to another. The mesh is represented as a triangulated mesh and deformations are modeled as triangle deformations. Deformation transfer commonly takes place on the mesh surface [1, 2, 3, 4], on a dual domain based on dual Laplacian coordinates [5], or on a lower dimensional embedded space [6, 7, 8, 9]. Techniques working directly on the surface produce a true copy of the original deformation example. However, they suffer low performance and slow convergence for dense meshes which are poorly sampled. Techniques based on lower dimensional space embeddings have a high performance and a fast convergence even with relative sparse meshes. However, they suffer a serious distortion with detailed deformations and it is difficult to construct an appropriate embedding space. Deforming on the dual domain can have a better performance than working directly on the surface and is able to handle sparse meshes.

All existent deformation transfer approaches use Euclidean representations for the triangle deformation and hence an excessive number of degrees of freedoms. One of the standard techniques in the graphics community is [1] which provides a faithful copy of triangular deformations [5]. The triangle deformation is defined by a (3×3) deformation matrix and a 3D displacement vector. Deformations outside the triangle plane are undefined, hence the nine dimensional space of deformations is under-constrained. They deal with this heuristically by adding a fourth virtual vertex defined by the cross product of two of the triangle edges. As a result, deformations may have zero or a negative determinant (inconsistent deformations), thus do not exclude non-physical deformations. Other methods [2, 3, 7, 6, 8, 5, 9] have variations on these representations on heuristics or the space to define the parameters

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but all of them finally use Euclidean representations of the deformation matrix. In this work, our objective is to use a true representation for non-rigid deformations and articulations which respects its underlying geometry.
The work of [10] proposed a manifold for shape representation where they represent human body shapes by using a Lie group of deformations. This Riemannian structure respects the geometry of the deformations space. It leads into eliminating redundant degrees of freedom in Euclidean representation of deformations, guarantees to use no heuristics in deformation composition and removes non-physical deformations which have negative or zero determinants. 3D shape processing takes place on the tangent space which is inherently Euclidean. Human poses are only introduced by means of interpolation/extrapolation in this tangent space.

The present work extends [10] to fit both human shapes and poses. We propose to represent new unseen poses on the manifold using the same Lie group of deformations for human shapes. Moreover, we give a novel deformation transfer approach directly expressed on the manifold with no need to lift up to the tangent space. The main contributions of this work are: (1) deformation transfer is defined on manifolds which respect the 3D human shape Riemannian structure, (2) the method guarantees to use no heuristics, remove inconsistent deformations, and use minimal required degrees of freedom, and (3) it is less computationally expensive as it can be parallelized, having the same process per triangle, and being performed directly on the manifold without lifting to the tangent space.

The paper is organized as follows: Section 2 presents the mathematical formulation of triangle deformation on manifolds. The novel deformation transfer on manifolds is explained in Section 3. The experimental results are reported in Section 4 and the work is finally concluded in Section 5.

2. MATHEMATICAL MODEL

We manipulate deformations on triangulated meshes where each 3D human body mesh is composed of N triangles. This work uses the Lie Bodies manifold representation of 3D triangulated bodies [10] and builds upon it. Hence, a similar mathematical model is adopted with new propositions. Below, we explain the considered triangle deformation representation.

A non-degenerate triangle can be defined by three vertices $\{v_0,\, v_1,\, v_2\} \subset \mathbb{R}^3$, and represented, without loss of generality, by its edge matrix $[v_1 - v_0,\, v_2 - v_0] \in \mathbb{R}^{3\times 2}$. Deforming a triangle T_1 by a deformation $D \in \mathbb{R}^{3\times 3}$ is not unique as the triangle $T_2 = DT_1$ has six constraints only. Some methods in the literature use heuristics, however [10] proposes working in a non-linear 6-dimensional (6D) space. The idea is based on the ability to deform T_1 to T_2 by combining isotropic scaling, in-plane deformation and a 3D rotation. These deformations overcome the problems of Euclidean deformations (e.g., having a negative determinant which represents non-physical deformations). The used deformations impose a group structure of three components. The first one is G_S which denotes $\mathbb{R}^+$, the group for isotropic scaling with a standard multiplication operation. The second component is G_P defined as:

$$G_P \triangleq \{P = \begin{pmatrix} 1 & F \\ 0 & H \end{pmatrix} : \, F \in \mathbb{R},\, H > 0\}. \qquad (1)$$

The third component is the rotation special orthogonal group of degree 3 denoted $SO(3)$ and defined as:

$$SO(3) = \{R : R^T R = I,\, \det(R) = +1\}, \qquad (2)$$

where $\det(\cdot)$ denotes the matrix determinant and ^{T} the matrix transpose. G_P and $SO(3)$ are subgroups of $GL(3)$, the general linear group of degree 3 which has the set of (3×3) real non-singular matrices, together with the operation of matrix multiplication. The two elements $P \in G_P$ and $S \in G_S$ act on a canonical triangle which is relaxed in this work by a new definition to work for arbitrary mesh triangles. P and S are computed using the input and deformed triangles [10].
A canonical triangle is represented by an edge matrix in which $[v_1 - v_0,\, v_2 - v_0] = [(x_1, 0, 0),\, (x_2, y_2, 0)]$, such that $x_1 > 0$ and $x_2, y_2 \in \mathbb{R}$. Given two canonical triangles C_1 and C_2, there exists a unique $(P, S) \in G_P \times G_S$ such that $C_2 = PSC_1$. A canonical triangle C can always be found by a rotation matrix $R_C \in SO(3)$ such that $C = R_C T$ is canonical and T is any triangle.
Finally, if T_1 and T_2 are any arbitrary triangles then there exist two rotation matrices R_1 and R_2 such that $R_2 T_2 = PSR_1T_1$. Hence, a triangle T_1 is deformed into T_2 as follows:

$$T_2 = R_2^T PSR_1T_1. \qquad (3)$$

There exists $R \in SO(3)$ such that $R_2^T = RR_1^T$, then $T_2 = RR_1^T PSR_1T_1$. The group $(R,\, P,\, S)$ has six degrees of freedom: 1 for S, 2 for P and 3 for R. We also have:

$$\det(RR_1^T PSR_1) = HS > 0, \qquad (4)$$

which is a (3×3) invertible matrix deforming T_1 to T_2 and has six degrees of freedom only. Having the determinant strictly positive removes any non-physical deformations like reflections. Now, we may define the triangle deformation group G_T as the set of R, P and S which is the direct product of $SO(3)$, G_P and G_S.

3. DEFORMATION TRANSFER ON MANIFOLDS

The Lie group of triangle mesh deformations can be defined as a smooth manifold $\mathcal{M} \triangleq G_T^N$ of dimension $6N$ where each mesh $\mathcal{S}_i^j$ is a set of N triangles. We write $\mathcal{S}_i^j = \{T_{(i,j)}^k,\, k = 1, ..., N\}$, such that i is the index for a given human body shape and j is the index for its current pose. Given a reference subject, $i = 0$, under two poses $j = 0$ and $j = 1$ represented by $\mathcal{S}_0^0$ and $\mathcal{S}_0^1$, respectively, our objective is to transfer the

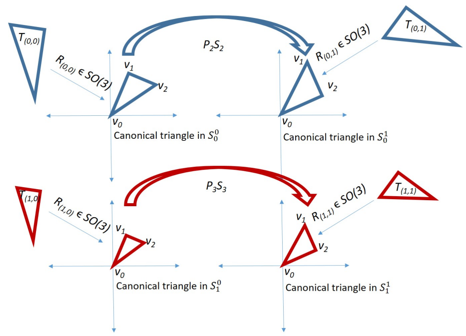

Fig. 2: Transfer of transformations on manifolds.

target pose corresponding to $j = 1$ to a new subject $i = 1$, for which only the mesh $\mathcal{S}_1^0$ for the initial pose is known, see Fig. 1. We assume that all input meshes are registered[1].
Considering (3), we may define three manifolds $\mathcal{M}_1, \mathcal{M}_2$, and $\mathcal{M}_3$ such that $\mathcal{S}_0^0, \mathcal{S}_1^0 \in \mathcal{M}_1$, $\mathcal{S}_0^0, \mathcal{S}_0^1 \in \mathcal{M}_2$, $\mathcal{S}_1^0, \mathcal{S}_1^1 \in \mathcal{M}_3$, and for all k, we have

$$\begin{cases} \mathcal{M}_1 : & \mathcal{S}_1^0 \ni T_{(1,0)}^k = (R_{(1,0)}^k)^T P_{\mathcal{M}_1}^k S_{\mathcal{M}_1}^k R_{(0,0)}^k T_{(0,0)}^k, \\ \mathcal{M}_2 : & \mathcal{S}_0^1 \ni T_{(0,1)}^k = (R_{(0,1)}^k)^T P_{\mathcal{M}_2}^k S_{\mathcal{M}_2}^k R_{(0,0)}^k T_{(0,0)}^k, \\ \mathcal{M}_3 : & \mathcal{S}_1^1 \ni T_{(1,1)}^k = (R_{(1,1)}^k)^T P_{\mathcal{M}_3}^k S_{\mathcal{M}_3}^k R_{(1,0)}^k T_{(1,0)}^k. \end{cases} \tag{5}$$

The transformations P and S as well as the rotations R for $\mathcal{M}_1$ and $\mathcal{M}_2$ can be computed from the available input meshes [10]. The goal is to estimate $\mathcal{S}_1^1$, which from (5), boils down to finding the transformations $R_{(1,1)}^k$, $P_{\mathcal{M}_3}^k$, and $S_{\mathcal{M}_3}^k$. The proposed solution is based on copying the deformation of the reference subject, $i = 0$, to the new subject, $i = 1$, which we translate to applying $P_{\mathcal{M}_2}^k S_{\mathcal{M}_2}^k$ on $\mathcal{S}_1^0$. The assumption is:

$$P_{\mathcal{M}_2}^k S_{\mathcal{M}_2}^k \cong P_{\mathcal{M}_3}^k S_{\mathcal{M}_3}^k, \quad \forall k. \tag{6}$$

The next step is to estimate the rotations $R_{(1,1)}^k$. Since $R_{(0,0)}^k$, $R_{(1,0)}^k$, $R_{(0,1)}^k$, and $R_{(1,1)}^k$ are all elements of $SO(3)$, then

$$\exists\, A^k \in SO(3) \quad \text{s.t.} \quad R_{(1,0)}^k = A^k R_{(0,0)}^k, \quad \forall k. \tag{7}$$

We assume that the same transformations A^k transform $R_{(0,1)}^k$ to $R_{(1,1)}^k$. We may then use $A^k = R_{(1,0)}^k (R_{(0,0)}^k)^T$ to estimate $R_{(1,1)}^k$ as:

$$\hat{R}_{(1,1)}^k = A^k R_{(0,1)}^k, \quad \forall k. \tag{8}$$

This can be thought of as having a parallel transfer of rotations on $SO(3)$, where A^k, $k = 1, \cdots, N$, transfer the canonical transformations $R_{(0,0)}^k$ of $\mathcal{S}_0^0$ to the canonical transformations $R_{(1,0)}^k$ of $\mathcal{S}_1^0$. This can be seen as parallel to the transfer from the $\mathcal{S}_0^1$ canonical transformations $R_{(0,1)}^k$ to the $\mathcal{S}_1^1$ canonical transformations $R_{(1,1)}^k$. A visual explanation of the considered assumptions is shown in Fig. 2. From equations (5), (6), and (8), we may compute an estimate of $\mathcal{S}_1^1$ as follows:

$$\hat{\mathcal{S}}_1^1 \ni \hat{T}_{(1,1)}^k = (A^k R_{(0,1)}^k)^T P_{\mathcal{M}_2}^k S_{\mathcal{M}_2}^k R_{(1,0)}^k T_{(1,0)}^k, \quad \forall k. \tag{9}$$

Finally, after applying (9) to estimate the triangles $\hat{T}_{(1,1)}^k$, $k = 1, \cdots, N$, the final estimated triangulated mesh $\hat{\mathcal{S}}_1^1$ is reconstructed using the same technique of [1, 12].

4. DISCUSSION AND RESULTS

Three datasets have been used for the evaluation: the SHREC synthetic dataset [11], the FAUST dataset of real scans [13], and 3D human meshes generated using the SMPL model [14]. The proposed method outperforms [1] in computing realistic 3D shape normals and poses. This can be seen in the light reflections on the meshes, plotted using MeshLab [15], as shown in Fig. 3 and Fig. 4. The first columns to the left in these figures show the input initial poses, also known as "rest" poses, and the first row shows the input target poses of the first subject to be transferred to the second subject. The unrealistic light reflections in the third row are due to having transformations with negative or zero determinants computed by [1]. Our result shows the same realistic light reflection pattern of the ground truth in the first rows and first columns in Fig. 3 and Fig. 4, which is a direct result of (4). The problem of having unrealistic poses with [1] can be clearly seen in the third row in Fig. 4. In general, our generated poses are closer to the original intended target poses. The slight differences, in Fig. 4, between the second and third rows compared to the first row are the direct interpretation of having the initial rest poses different from each other, see Fig. 5.
In order to evaluate the accuracy of the proposed method, we use the SHREC dataset [11] and the SMPL model [14] to generate synthetic meshes with accurate ground truth. Unfortunately, the FAUST dataset [13] can not be used for a quantitative comparison because all its initial rest poses are not iden-

Fig. 4: Comparison with [1] on the FAUST dataset [13]. 1^{st} column: rest poses, the 1^{st} row: Ground truth target poses, 2^{nd} row: our results, 3^{rd} row: results of [1].

[1] Note that the same work is applicable to any triangulated meshes, and not limited to human bodies.

Fig. 3: Comparison of the proposed deformation transfer on manifolds to the work of [1] on the SHREC dataset [11]. 1^{st} column: input rest poses; 1^{st} row: target poses to be transferred to the 2^{nd} subject.2^{nd} row: our results. 3^{rd} row: results of [1].

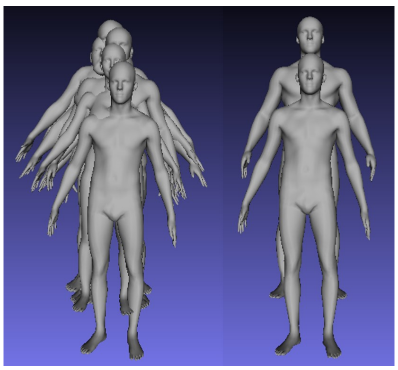

Fig. 5: Rest poses for the FAUST dataset. Left: all poses, right: poses used in Fig. 4.

Fig. 6: Generated meshes using SMPL [14]. Left: ground truth, right: example of input (top) and our result (bottom).

tical, see Fig. 5. Hence, this difference will naturally propagate into the output deformation in any deformation transfer method, see Fig. 4. This directly results in having unreliable ground truth meshes for FAUST dataset to compute the deformation error. The computed mean error, between the ground truth 3D points and the reconstructed 3D points of the deformed meshes for the SHREC dataset is very close to zero (10^{-15}) after centering to a zero mean and normalizing to a unit norm. Our method produces physically correct poses with correctly computed normals as shown in Fig. 3 and Fig. 4. The third pose from the left at the bottom in Fig. 4 can give a good view of serious errors to be avoided in real data using the proposed method. We have generated 3D human shapes and poses using the SMPL parametric model [14] for male and female subjects, see Fig. 6. On the left hand-side, the generated meshes using SMPL [14] are shown. Three poses are generated for each subject: the rest pose and two random poses. The same poses are generated for two males (first two rows) and two females (last two rows). Each input rest pose in the first column has been transferred to the other two poses of the three other persons. An example of the ground truth pose (top) and the output from our method (bottom) is shown on the right hand-side. As expected, the mean error is very close to zero as the generated meshes and poses are far less complex than the SHREC dataset in terms of poses and mesh resolution. Each mesh in SHREC is composed of 59727 vertices and 119344 faces (triangles) while each mesh in the generated models using SMPL is composed of 6890 vertices and 13776 faces.

5. CONCLUSION

This work proposes a novel technique to copy deformations on manifolds in a closed form. It works on triangulated meshes which are the most common representation for 3D meshes. This automatic copy of transformations saves a huge amount of manual efforts and time. The main advantages of our technique are: (1) it uses the minimal required number of degrees of freedom for deformations as opposed to Euclidean space based deformations, (2) the deformations have positive determinants which guarantees consistent deformations (only physically plausible deformations are allowed), (3) it does not need heuristics to compute the deformations to solve the ambiguity in the space perpendicular to the triangle plane, and (4) the technique is less computationally expensive as it takes place directly on the manifold without lifting up to the tangent space. Our method outperformes [1] in terms of having realistic deformations where only physically correct deformations are allowed.

6. REFERENCES

[1] Robert W. Sumner and Jovan Popović, "Deformation transfer for triangle meshes," *ACM Trans. Graph.*, vol. 23, no. 3, pp. 399–405, Aug. 2004.

[2] Rhaleb Zayer, Christian Rössl, Zachi Karni, and Hans-Peter Seidel, "Harmonic guidance for surface deformation," *Comput. Graph. Forum*, vol. 24, no. 3, pp. 601–609, 2005.

[3] Ilya Baran, Daniel Vlasic, Eitan Grinspun, and Jovan Popović, "Semantic deformation transfer," *ACM Trans. Graph.*, vol. 28, no. 3, pp. 36:1–36:6, July 2009.

[4] Kun Zhou, Weiwei Xu, Yiying Tong, and Mathieu Desbrun, "Deformation transfer to multi-component objects," *Comput. Graph. Forum*, vol. 29, no. 2, pp. 319–325, 2010.

[5] Yong Zhao, Bin Pan, Chunxia Xiao, and Qunsheng Peng, "Dual-domain deformation transfer for triangular meshes," *Comput. Animat. Virtual Worlds*, vol. 23, no. 3-4, pp. 447–456, May 2012.

[6] Yong Zhao, Xinguo Liu, Chunxia Xiao, and Qunsheng Peng, "A unified shape editing framework based on tetrahedral control mesh," *Comput. Animat. Virtual Worlds*, vol. 20, pp. 301–310, June 2009.

[7] Mirela Ben-Chen, Ofir Weber, and Craig Gotsman, "Spatial deformation transfer," in *Proceedings of the 2009 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, New York, NY, USA, 2009, SCA '09, pp. 67–74, ACM.

[8] Lu Chen, Jin Huang, Hanqiu Sun, and Hujun Bao, "Cage-based deformation transfer," *Computers & Graphics*, vol. 34, no. 2, pp. 107–118, 2010.

[9] Chin-chia Tung, Tsung-Hua Li, Hong Shiang Lin, and Ming Ouhyoung, "Cage-based deformation transfer using mass spring system," in *Special Interest Group on Computer Graphics and Interactive Techniques Conference, SIGGRAPH '14, Vancouver, Canada, August 10-14, 2014, Posters Proceedings*, 2014, p. 34:1.

[10] Oren Freifeld and Michael J. Black, "Lie bodies: A manifold representation of 3d human shape," in *Proceedings of the 12th European Conference on Computer Vision - Volume Part I*, Berlin, Heidelberg, 2012, ECCV'12, pp. 1–14, Springer-Verlag.

[11] Z. Lähner, E. Rodolà, M. M. Bronstein, D. Cremers, O. Burghard, L. Cosmo, A. Dieckmann, R. Klein, and Y. Sahillioglu, "Shrec' 16: Matching of deformable shapes with topological noise," in *Proc. of Eurographics Workshop on 3D Object Retrieval (3DOR)*, 2016.

[12] Dragomir Anguelov, Praveen Srinivasan, Daphne Koller, Sebastian Thrun, Jim Rodgers, and James Davis, "Scape: Shape completion and animation of people," *ACM Trans. Graph.*, vol. 24, no. 3, pp. 408–416, July 2005.

[13] Federica Bogo, Javier Romero, Matthew Loper, and Michael J. Black, "FAUST: Dataset and evaluation for 3D mesh registration," in *Proceedings IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, Piscataway, NJ, USA, June 2014, IEEE.

[14] Matthew Loper, Naureen Mahmood, Javier Romero, Gerard Pons-Moll, and Michael J. Black, "Smpl: A skinned multi-person linear model," *ACM Trans. Graph.*, vol. 34, no. 6, pp. 248:1–248:16, Oct. 2015.

[15] Paolo Cignoni, Marco Callieri, Massimiliano Corsini, Matteo Dellepiane, Fabio Ganovelli, and Guido Ranzuglia, "Meshlab: an open-source mesh processing tool," in *Eurographics Italian Chapter Conference*, 2008.