

# DEFORMATION TRANSFER OF 3D HUMAN SHAPES AND POSES ON MANIFOLDS

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## ABSTRACT

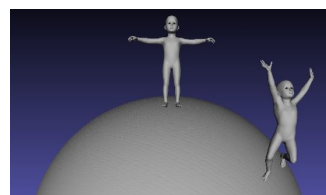
In this paper, we introduce a novel method to transfer the deformation of a human body to another directly on a manifold. There exists a rich literature on transferring deformations based on Euclidean representations. However, a 3D human shape and pose live on a manifold and have a Riemannian structure. 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.

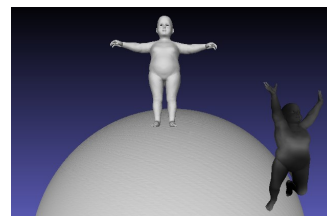
## 1. INTRODUCTION

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



(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].

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  $(3 \times 3)$  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:

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

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

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

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  $(3 \times 3)$  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  $R_2 T_2 = PSR_1 T_1$ . Hence, a triangle  $T_1$  is deformed into  $T_2$  as follows:

$$T_2 = R_2^T PSR_1 T_1. \quad (3)$$

There exists  $R \in SO(3)$  such that  $R_2^T = RR_1^T$ , then  $T_2 = RR_1^T PSR_1 T_1$ . The group  $(R, P, S)$  has six degrees of freedom: 1 for  $S$ , 2 for  $P$  and 3 for  $R$ . We also have:

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

which is a  $(3 \times 3)$  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  $\mathcal{S}_i^j = \{T_{(i,j)}^k, k = 1, \dots, N\}$ , 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

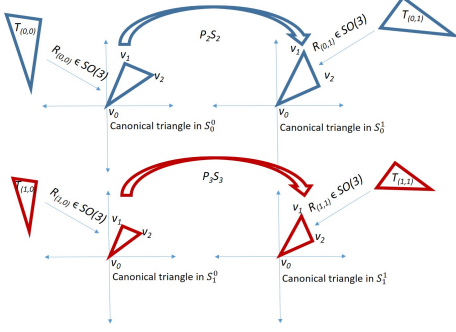


Fig. 2: Transfer of transformations on manifolds.

target pose corresponding to  $j = 1$  to a new subject  $i = 1$ , for which only the mesh  $S_1^0$  for the initial pose is known, see Fig. 1. We assume that all input meshes are registered<sup>1</sup>. Considering (3), we may define three manifolds  $\mathcal{M}_1, \mathcal{M}_2$ , and  $\mathcal{M}_3$  such that  $S_0^0, S_1^0 \in \mathcal{M}_1$ ,  $S_0^0, S_1^0 \in \mathcal{M}_2$ ,  $S_1^0, S_1^1 \in \mathcal{M}_3$ , and for all  $k$ , we have

$$\begin{cases} \mathcal{M}_1 : S_1^0 \ni T_{(1,0)}^k = (R_{(1,0)}^k)^T P_{\mathcal{M}_1}^k S_{\mathcal{M}_1}^k R_{(0,0)}^k T_{(0,0)}^k, \\ \mathcal{M}_2 : S_0^1 \ni T_{(0,1)}^k = (R_{(0,1)}^k)^T P_{\mathcal{M}_2}^k S_{\mathcal{M}_2}^k R_{(0,0)}^k T_{(0,0)}^k, \\ \mathcal{M}_3 : S_1^1 \ni T_{(1,1)}^k = (R_{(1,1)}^k)^T P_{\mathcal{M}_3}^k S_{\mathcal{M}_3}^k R_{(1,0)}^k T_{(1,0)}^k. \end{cases} \quad (5)$$

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  $S_1^1$ , 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  $S_1^0$ . The assumption is:

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

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

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

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:

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

This can be thought of as having a parallel transfer of rotations on  $SO(3)$ , where  $A^k$ ,  $k = 1, \dots, N$ , transfer the canonical transformations  $R_{(0,0)}^k$  of  $S_0^0$  to the canonical transformations  $R_{(1,0)}^k$  of  $S_1^0$ . This can be seen as parallel to the transfer from the  $S_0^0$  canonical transformations  $R_{(0,1)}^k$  to the  $S_1^1$  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  $S_1^1$  as follows:

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

Finally, after applying (9) to estimate the triangles  $\hat{T}_{(1,1)}^k$ ,  $k = 1, \dots, N$ , the final estimated triangulated mesh  $\hat{S}_1^1$  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-

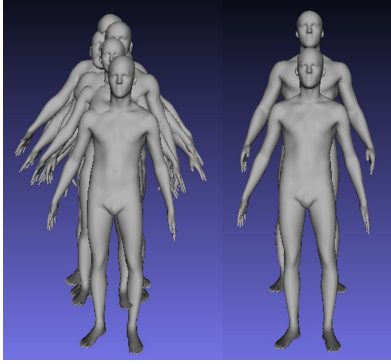


Fig. 4: Comparison with [1] on the FAUST dataset [13]. 1<sup>st</sup> column: rest poses, the 1<sup>st</sup> row: Ground truth target poses, 2<sup>nd</sup> row: our results, 3<sup>rd</sup> row: results of [1].

<sup>1</sup>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<sup>st</sup> column: input rest poses; 1<sup>st</sup> row: target poses to be transferred to the 2<sup>nd</sup> subject. 2<sup>nd</sup> row: our results. 3<sup>rd</sup> row: results of [1].



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

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



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

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 outperforms [1] in terms of having realistic deformations where only physically correct deformations are allowed.

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