Compression and Completion of Animated Point Clouds using Topological Properties of the Manifold

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Introduction

Goal

- Redundant point cloud data ➔ data compression
- Incomplete point cloud data ➔ data completion

- A new method that can distinguish body parts and factorize the data into shape and pose purely using topological properties of the manifold.

Approach

we formulate the deformation distance between two points tracks as the smallest deformation along the path between them. After embedding such distance in low dimensional space, a clustering of embedded data leads to close to rigid components, suitable as initialization for fitting a skinned rigged mesh. As both local deformations and neighborhoods of a point are local and can be estimated only from the part of the animation, the method can be used to recover unobserved data in each frame.

Methodology

Relative deformation calculation

- Neighbors (if $\forall k: \left|x_i^k - x_j^k\right| < \epsilon$)

$$t_i^{kl} = arg\min_{T'} \sum_{j \in N_i} \left|\left|x_j^l - T' x_j^k\right|\right|_0$$

$$d^{kl}(i,j) = \left|t_i^{kl}, t_j^{kl}\right|$$

$$\overline{d_{ij}} = \sum_{(k,l) \in P} d^{kl}(i,j)$$

where $||.||_0$ is an L_0 pseudo-norm maximizing the number of inliers within a certain small threshold and can be estimated using RANSAC

- Non-neighbors

$$\overline{d_{ij}} = \sum_{a \in \{1..A-1\}} \overline{d_{p(a),p(a+1)}}$$

where $(p(1), p(2)..p(A))$ is the shortest path with respect to the deformation measure between points $p(1) = i$ and $p(T) = j$.

Low-dimensional embedding

- ISOMAP dimensionality reduction
- Landmark IOSMAP speedup
- Clustering to get limbs

Skinned rigged mesh recovering

- A static template $x_m^{(k)}$ for each cluster $(x_m^{(1)} = x_m^1)$
- Alignment calculation

$$T_m^k = arg\min_{T'} \sum_{k \in \{1..K\}} \sum_{i \in \mathbf{x}_m} \left|\left|T'^{-1} x_i^k - x_i^{(k-1)}\right|\right|_0$$

where $||.||_0$ is an L_0 pseudo-norm maximizing the number of inliers within a certain small threshold and can be estimated using RANSAC.

- Template update

$$x_m^{(k)} = \frac{k-1}{k} x^{(k-1)} + \frac{1}{k} \left(T_m^k\right)^{-1} x_m^{(k-1)}$$

- Weights associations

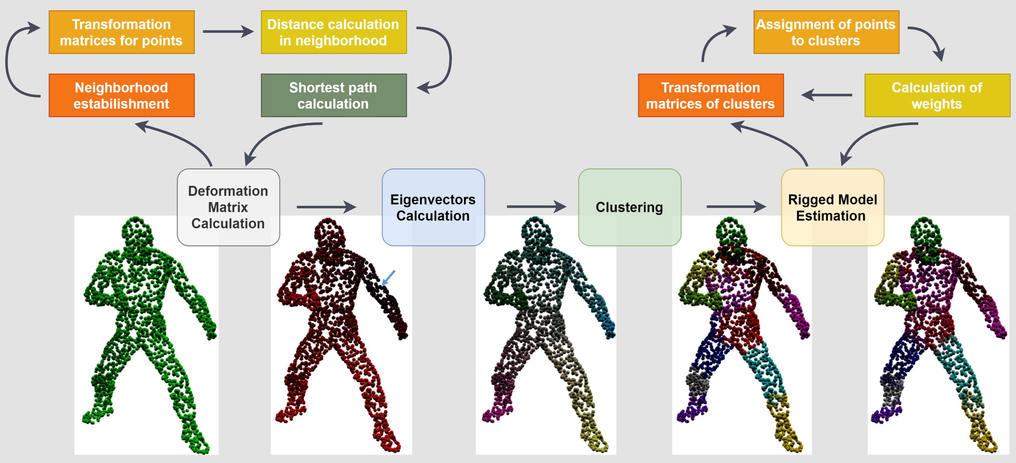
$$\underset{w_i'}{\text{minimize}} \quad \sum_{k \in \{1..K\}} \left(\sum_{m \in \{1..M\}} w'_{im} T_m^k x_i - x_i^k \right)^2$$

$$\text{subject to} \quad w'_{im} \geq 0 \text{ and } \sum_{m \in \{1..M\}} w'_{im} = 1$$

3D data completion

- Modify to only take visible frames into account

Pipeline



Robustness

noise	mean ± SD	median
0.000	0.02415 ± 0.01200	0.02086
0.002	0.02922 ± 0.02232	0.01991
0.010	0.03359 ± 0.01982	0.02708
0.020	0.03318 ± 0.01409	0.02991
0.030	0.04461 ± 0.02285	0.03867
0.040	0.04503 ± 0.01882	0.04169

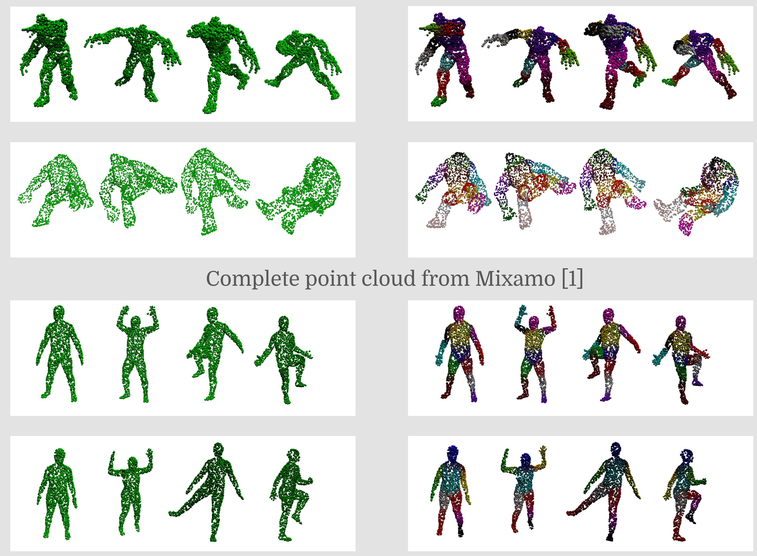
- Gaussian noise is added to the input.
- The reconstruction error converges to the level of noise with the increase of noise

References

[1] Characters from www.mixamo.com
[2] Characters from DFAUST (F. Bogo, J. Romero, G. Pons-Moll, and M. J. Black. Dynamic faust: Registering human bodies in motion. Conference on Computer Vision and Pattern Recognition, 2017. 1)

Experiments

Compression

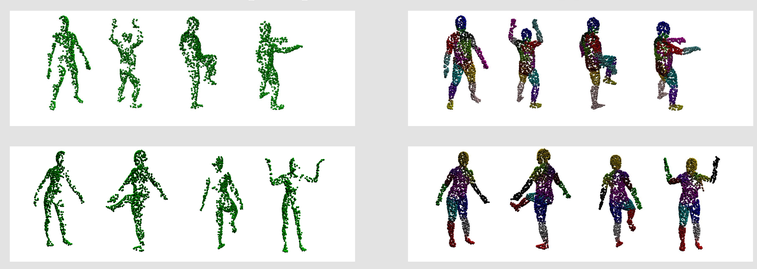


Complete point cloud from Mixamo [1]

Complete point cloud from DFAUST [2]

Completion

Incomplete point cloud from Mixamo [1]



Incomplete point cloud from DFAUST [2]