Motion Compression using Principal Geodesics Analysis

Maxime Tournier,[1] Lionel Reveret,[1] Xiaomao Wu,[1] Nicolas Courty,[2] Elise Arnaud[1]
[1]INRIA, University of Grenoble, France
[2]University of Bretagne Sud, France

Goal

Motivation

Motion capture data are big, yet show a high degree of **temporal and spatial coherence** . We exploit these for compression purposes by building a model of the joints' orientations. This pose model is used in an inverse kinematics algorithm to recover poses from end-effectors positions.

Contributions

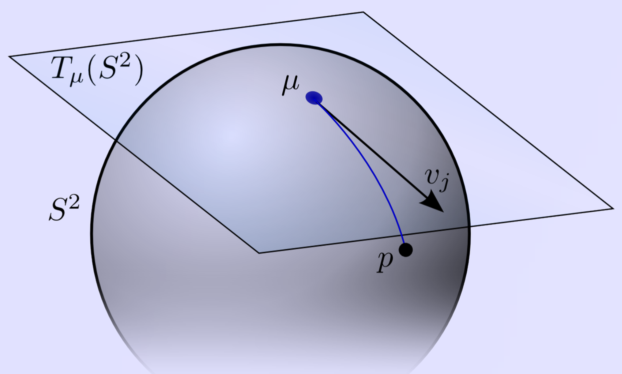
- An efficient, lossy compression technique for motion capture data
- An interactive, data-driven Inverse Kinematics algorithm
- A compact and easily editable motion representation

Principal Geodesics Analysis

Principal Geodesics Analysis (PGA, [FLJ03]) extends Principal Component Analysis (PCA) for more abstract manifolds, such as the rotations space $SO(3)$

- The data are projected onto ***geodesics*** rather than straight lines
- The data are then recovered by "flowing" over each geodesic using the exponential map, starting at the intrinsic mean of the data:

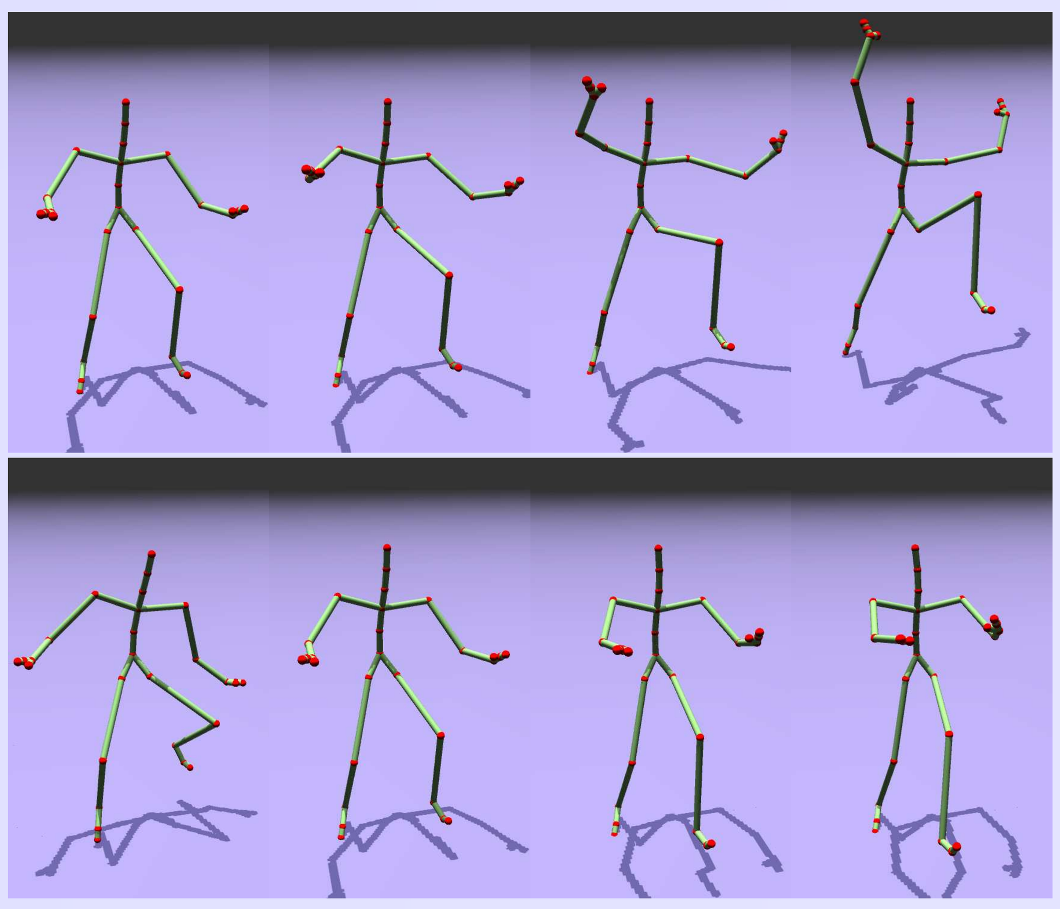
$$p = \mu . \prod_{j=1}^{j=k} e^{t_j . v_j}$$



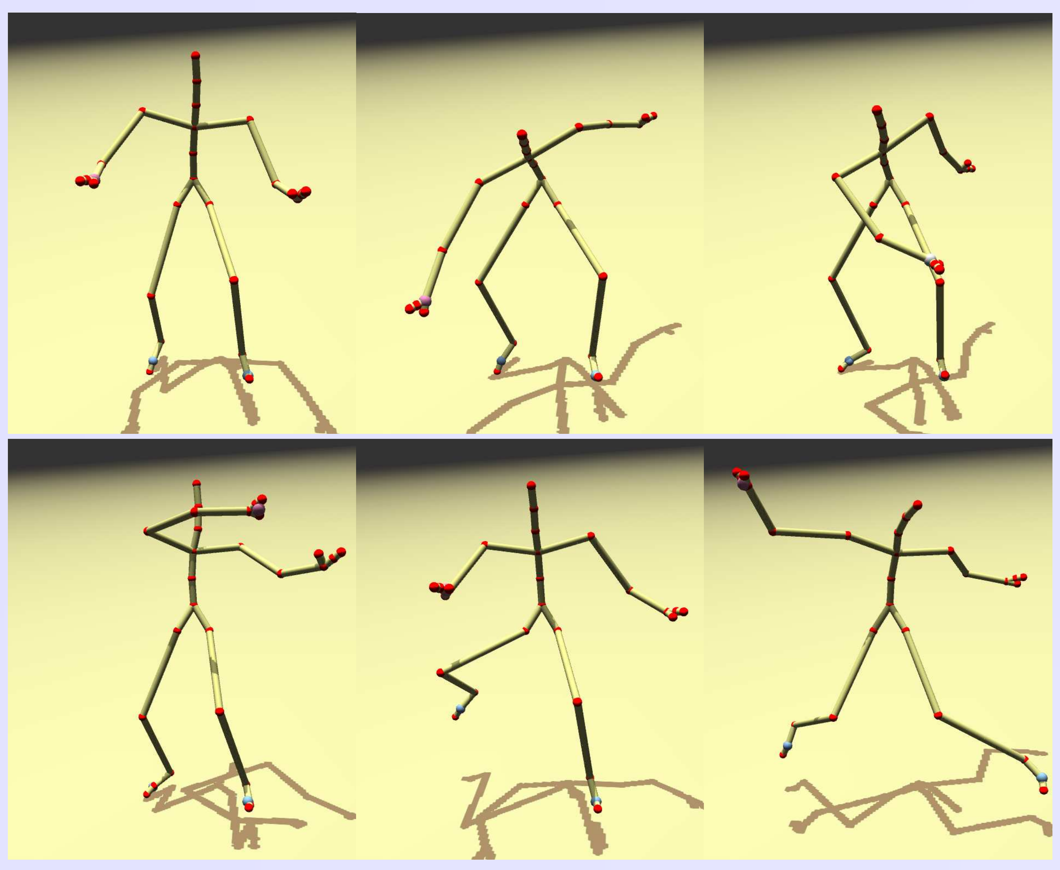
PGA may be approximated by a PCA in the tangent space at the intrinsic mean of the data μ.

PGA-based Inverse Kinematics

Motion modes
From one motion, we compute k principal geodesics out of the **joints orientation** data. These motion modes provide a *reduced pose parametrization* of the input motion.



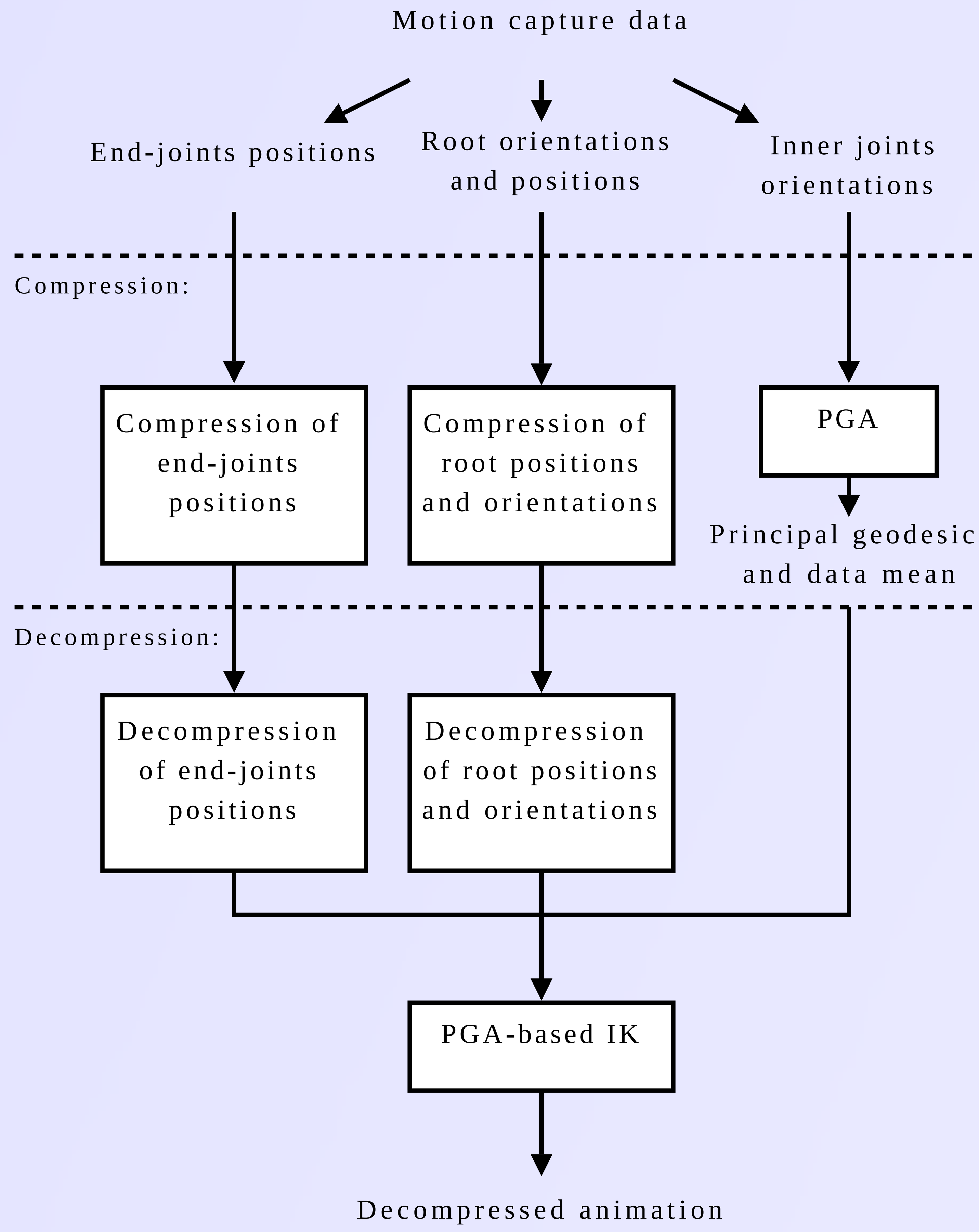
Data-driven Inverse Kinematics
We optimize the geodesic coefficients to match end-effectors constraints in order to perform inverse kinematics (IK). The resulting poses are composed of motion modes extracted using PGA, thus **exhibit the correlations present in the input motion**.



Poses recovery
Given k geodesics, we recover poses using only the end-effectors' positions ⇒ **compression**

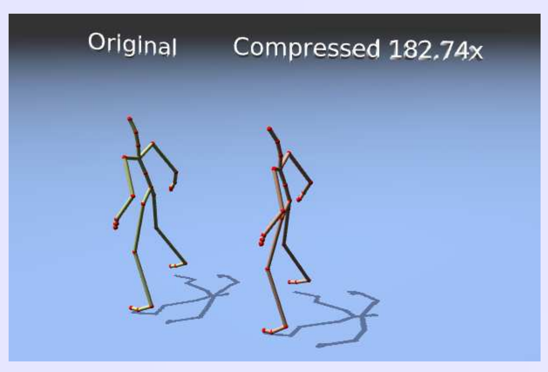
Compression Pipeline

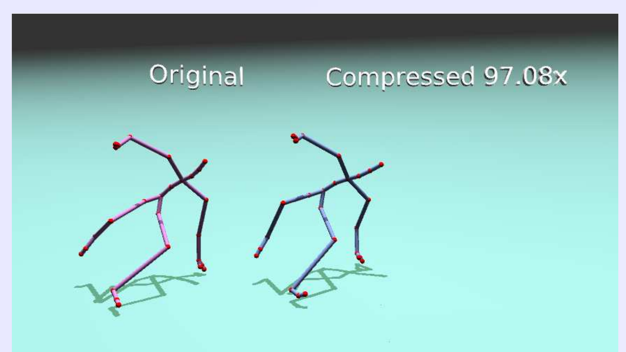
Using the PGA-based IK, we recover each frame from the end-effectors positions. We exploit temporal coherence in the end-effectors' position by compressing them with spline interpolation.



Results

+ **High compression rates** with few visual distortion ($d = 100 \frac{\|A - \tilde{A}\|}{\|A - E(A)\|}$)
+ **Easily editable** motion representation
− Decompression is slower than other techniques (yet realtime)





1:182	Compression ratio	1:97
0.049	Distortion rate d	0.56
16.2	Decompression time (msec/frame)	20.42

References

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