Enhancing Spatial Keyframe Animations with Motion Capture

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Abstract: While motion capture (*mocap*) achieves realistic character animation at great cost, keyframing is capable of producing less realistic but more controllable animations. In this paper we show how to combine the Spatial Keyframing Framework (*SKF*) of Igarashi et al.(Igarashi et al., 2005) and multidimensional projection techniques to reuse mocap data in several ways. For instance, by extracting meaningful poses and projecting them on a plane, it is possible to sketch new animations using the SKF. Additionally, we show that multidimensional projection also can be used for visualization and motion analysis. We also propose a method for mocap compaction with the help of SK's pose reconstruction (backprojection) algorithm. This compaction scheme was implemented for several known projection schemes and empirically tested alongside traditional temporal decimation schemes. Finally, we present a novel multidimensional projection optimization technique that significantly enhances SK-based compaction and can also be applied to other contexts where a back-projection algorithm is available.

1 INTRODUCTION

Character animation focuses on bringing life to a particular character model. There are several ways of animating a character in a scene. One popular way is rigging a skeleton to a character model (a skin) such that when the skeleton pose is changed, so does the model. This binds the character movements to the degrees of freedom (DOF) of this skeleton.

In standard keyframe-based animation, some key poses are created by artists and interpolated at each frame, sometimes using manually adjusted Bézier curves. However, for complicated or extended animations, this process turns out to be difficult and time-consuming. As an alternative, the approach known as *motion capture* or *mocap* was developed. In it, a human actor wearing a special suit performs movements which are recorded by a set of cameras and sensors. After some processing, it is possible to build a complete description of the actor's movement in the form of a set of skeleton poses and positions sampled with high precision, both in time and space. A typical mocap file has a description of the skeleton's shape and articulations, together with a set of poses, each containing a timestamp, the rotation of each joint and a translation vector of the root joint with respect to a standard rest pose.

Another animation authoring framework called *spatial keyframing* (SK) was proposed by Igarashi et al. (Igarashi et al., 2005). The main idea is to associate keyframes (poses) to carefully placed points on a plane rather than to points in time. Although simple in thesis, spatial keyframing still requires keyframe poses to be authored manually, which is a time-consuming task when many such poses are required or when the skeleton contains many joints. One way to help the process, therefore, is to harvest interesting poses from raw mocap files. The present work investigates algorithms and techniques to accomplish just that. Moreover, we propose using multidimensional projection techniques to automatically suggest an optimal placement for the spatial keyframes on the plane.

Another benefit of finding a good method to project points in pose space to a plane is that it also serves as a tool for the analysis of mocap files. The idea is that the movement contained in a mocap can be visualized as a trajectory in 2D space. Since a good projection method ensures that similar poses are projected onto points close to each other, the plane itself can be viewed as a pose similarity space. Thus, for instance, a cyclic movement is commonly projected onto a closed curve.

Finally, multidimensional projection of mocap data can be used as a tool for motion compression. Since mocap files ordinarily contain in excess of

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60 frames per second, a common lossy compression scheme consists of selecting important frames and reconstructing the complete motion by interpolation. Although this interpolation is frequently conducted using time as parameter, we show how spatial keyframing can be adapted for this purpose.

In a nutshell, this paper presents the following contributions:

1. Repurposes multidimensional visualization techniques to the problem of selecting key poses from mocap data and project them on a plane so that they can be used in the Spatial Keyframe animation Framework (SKF).
2. Shows how multidimensional projection can be used as a visual aid in the analysis of mocap data.
3. Empirically evaluates several multidimensional projection schemes in their application to mocap data.
4. Describes the use of SKF in compressing mocap data through decimation and reconstruction and, in particular, introduces a non-linear projection optimization algorithm that yields smaller reconstruction errors. This algorithm is not specific to mocap data, but can also be used with other data, provided a backprojection algorithm and an error metric are available.

2 RELATED WORK

In this section, we review the literature from areas related to the present work.

2.1 Pose Selection and Information Extraction

Decimating irrelevant poses from mocap data is a common way to produce a compact representation of a movement. The reconstruction of the original data is done by interpolating the small subset of poses that survive this decimation process. Since these play the same role of keyframes used in keyframe-based animation, the process is also called keyframe extraction.

A popular idea for extracting keyframes is curve simplification. Lim and Thalmann (Lim and Thalmann, 2001) view mocap data as a curve parameterized by time and propose using a technique (Lowe, 1987) for approximating such curves with a polygonal line. Later, this algorithm became known as simple curve simplification (SCS). This idea was later enhanced by Xiao et al. (Xiao et al., 2006) by employing an optimized selection strategy, which they named layered curve simplification (LCS). Both of these start with a minimal subset of the original mocap data and try to repeatedly select relevant keyframes by measuring the similarity between a local interpolation and the original frame. On the other hand, Togawa and Okuda (Togawa and Okuda, 2005) start with the full set and iteratively discard frames which least contribute to the interpolation, naming their contribution as position-based (PB) strategy.

Other possible approaches include clustering methods and matrix factorization. Clustering methods divide frames into clusters and search for a representative frame in each group. The works of Bulut and Capin (Bulut and Capin, 2007) and Halit and Capin (Halit and Capin, 2011) fall in this category. Both also consider dynamic information in the clustering metrics. Matrix factorization uses linear algebra methods to reconstruct mocap data represented in matrix format. Examples of such algorithms are the work of Huang et al. (Huang et al., 2005), called *key probe*, and that of Jin et al. (Jin et al., 2012).

2.2 Multidimensional Projection

The key motivation behind the use of dimensionality reduction approaches in this paper is that much of the redundancy found in mocap data can be attributed to DOFs that are hierarchically or functionally related. Note that in the context of this work, the terms “dimension reduction” and “multidimensional projection” are used interchangeably. Arikan (Arikan, 2006) proposes to use principal component analysis (PCA) on mocap data, together with clustering, to get a good rate of compaction. Halit and Capin (Halit and Capin, 2011), Safonova et al. (Safonova et al., 2004) and Jin et al.(Jin et al., 2012) also use PCA as a way to lower the data dimensionality and save computing time.

Zhang and Cao (Zhang and Cao, 2015) and Jin et al. (Jin et al., 2012) use locally linear embedding (LLE) (Roweis and Saul, 2000), a dimension reduction tool, to ease their search for keyframes in the frame set. LLE tries to find a projection where relative distances between each point and their nearest neighbors in lower dimension space is preserved in the least squares sense. The number of nearest neighbors is a parameter of the algorithm.

Assa et al.(Assa et al., 2005) also project the motion curve onto a 2D space to find keyframe candidates. They use a variant of multidimensional scaling (MDS) (Cox and Cox, 2008) to project the motion curve. MDS tries to find a projection such that relative distances in lower dimension space are as close as possible to the corresponding distances in the original space in the least squares sense. The distance definition is a parameter to be chosen. If the euclidean distance is chosen, MDS turns to produce the same result as PCA. Jenkins and Matarić (Jenkins and Matarić, 2004) use another MDS sibling method called Isomap (Tenenbaum et al., 2000) to reduce human motion to a smaller dimension for clustering purposes. Isomap turns to be MDS with geodesic distance as its distance definition.

It is worth noting that dimension reduction techniques such as PCA, MDS and LLE, besides being used for compaction, can also be employed for other purposes, most notably for visualization of multidimensional data. For instance, Tejada el al. (Tejada et al., 2003) developed a fast iterative approach to project multidimensional data onto a 2D space, based on neighborhood relationships. This approach is not guaranteed to be optimal but has been shown to produce interesting results for data visualization. Another dimension reduction technique aimed at visualization of multidimensional data is the t-Distributed Stochastic Neighborhood Embedding (t-SNE) (van der Maaten and Hinton, 2008).

Joia et al. (Joia et al., 2011) created the so-called local affine multidimensional projection (LAMP), where a small subset of points – called control points – are randomly picked from the original set and projected using some projection algorithm, whereas the remaining points are projected by means of an affine map expressed in terms of their distance to the control points in the original space. The control points can be moved on the projection plane and thus affect the projection of the whole set.

Amorim et al. (Amorim et al., 2014) propose another two-step projection approach which is similar to LAMP, but the affine map is replaced by radial basis functions (RBFs) (Dinh et al., 2002). In this projection scheme – RBFP for short – control point selection is aided by a technique called regularized orthogonal least squares (ROLS), a more elaborate approach compared to the random selection of LAMP. Notice that RBFs have an advantage over affine maps in the sense that they provide a smoother interpolation.

2.3 Backward Projection

"Unprojection" or backward projection is a less developed field compared to dimension reduction. It aims at producing points in the original multidimensional space which do not belong to the input data set. For instance, the iLAMP (dos Santos Amorim et al., 2012) approach uses the same LAMP(Joia et al., 2011) heuristic to get a backward projection, swapping high dimension with lower dimension. Amorim et al. (Amorim et al., 2015) use RBF interpolation to transport information from the reduced dimension to the original space. Their work aims at exploring facial expression generation interpolated from a set of control points selected with specialized heuristics.

Igarashi et al. (Igarashi et al., 2005) also use RBF interpolation to back-project a 2D point onto a multidimensional skeleton pose, as a way to provide a rapid prototyping environment for animators. In this scheme, each input skeleton pose is modeled and associated with a *marker point* manually placed on a plane. The idea is to build an RBF which maps any point on the plane to a pose smoothly interpolated from the marker point poses.

3 MOCAP COMPACTION

In this section we discuss the problem of mocap compaction (or compression), i.e., the problem of representing the data for a mocap session with only a few of the original poses. A compression scheme is a coupling between a pose selection strategy and a pose interpolation (or reconstruction) algorithm. We distinguish two broad classes of mocap compression approaches. The first, what we may call the "traditional" approach, consists of selecting a few representative poses from the original set – the keyframes – while the reconstruction uses time as the interpolating parameter. The second approach also selects representative poses, but uses multidimensional projection, so that all poses are mapped to points in 2D, while the reconstruction uses the 2 coordinates of this space as interpolating parameters. This way, we could consider the selected poses for schemes in the first approach as *temporal keyframes* while those for the second approach could be more properly called *spatial keyframes*.

3.1 Temporal Keyframe Schemes

The idea for these schemes is to obtain a compressed representation of the original mocap data by carefully selecting a subset of poses, with their attached timestamps, as shown in Fig. 2. Let the original mocap contain n poses $\mathbb{F} = \{p_1, p_2, \ldots, p_n\}$ uniformly spaced in time, and let the compressed representation consisting of a list with $m < n$ *keyframe* poses $\mathbb{G} = \langle p_{i_1}, p_{i_2}, \ldots, p_{i_m} \rangle$ and a list of the corresponding timestamp indices $\mathbb{T} = \langle i_1, i_2, \ldots, i_m \rangle$. Then, in order to reconstruct a pose p_j not in $\mathbb{G}$ we first find the two closest poses p_{i_k} and $p_{i_{k+1}}$ in $\mathbb{G}$ so that $i_k < j < i_{k+1}$. Thus, the reconstructed pose p'_j can be obtained by linear interpolation of p_{i_k} and $p_{i_{k+1}}$. It is also possible

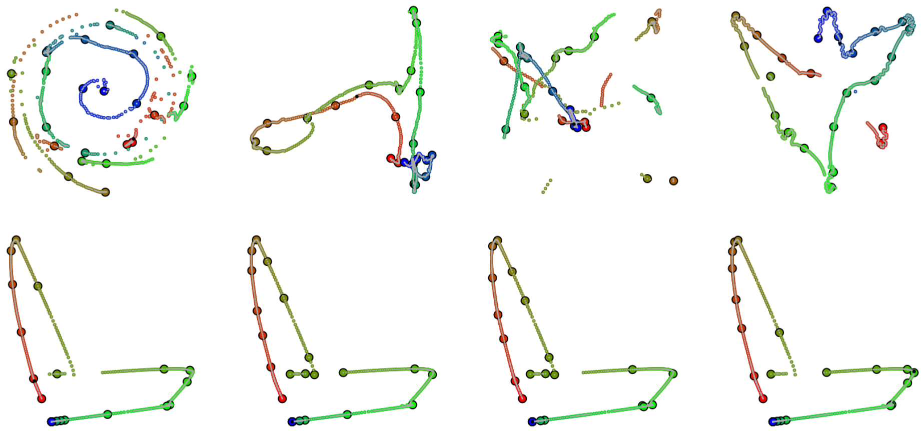


Figure 1: Implemented projection and keyframe extraction algorithms. Results obtained by projecting the poses in file `05_10.bvh` from the CMU Motion Capture database. The color gradient from red to green to blue is used to indicate time. Bigger dots with black border are keyframe poses (markers). First row from left to right: Force, MDS, PCA and t-SNE, where 3% of the poses are selected as keyframes by uniform sampling (US). Second row shows the results for LLE with keyframes selected with US, SCS, PB and ROLS.

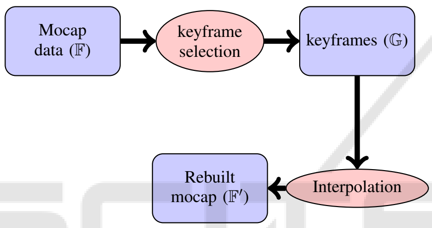


Figure 2: Workflow for a temporal mocap compression and reconstruction scheme.

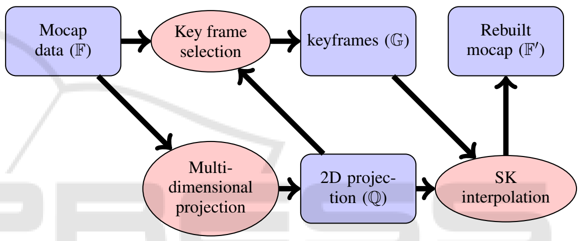


Figure 3: Workflow for mocap compression and reconstruction with spatial keyframes.

to use a higher order function for interpolation, like a cubic hermite curve, if we add the tangent at p_{i_k} and $p_{i_{k+1}}$. In fact, in addition to these two, it is also possible to use infinite support reconstruction functions (RBFs, say), which use all of $\mathbb{G}$.

3.2 Spatial Keyframe Schemes

Time is a natural interpolating domain for mocap data, since successive poses are necessarily similar due to physics constrains. We may, however, imagine an artificial "similarity" domain where two closely related poses are mapped to a pair of close points. We propose constructing such a domain by using multidimensional projection techniques. Thus, we propose adding to the keyframing pipeline a step where poses are first projected onto a plane. A skeleton pose is understood as a vector in high dimensional space, so that a sequence of projected poses with their corresponding timestamps can be regarded as a 2-dimensional trajectory representing the motion. This trajectory can be used to recover the original data with the help of a back-projection algorithm. We adopt the algorithm from Igarashi et al.(Igarashi et al., 2005) to recover the multidimensional pose from the projected pose, since this algorithm was specifically devised for this kind of data.

Fig. 3 illustrates the workflow for such schemes. Mocap data will feed a keyframe selection algorithm, just as in a temporal scheme, but an additional step is required, where a multidimensional projection algorithm is used to project all poses onto a plane. Thus, in addition to a set $\mathbb{G}$ of keyframes, the compressed representation also includes set $\mathbb{Q} = \{q_1, q_2, \ldots, q_n\}$, where q_i represents a projection of p_i.

We should also distinguish common projection approaches from those employing control points, such as LAMP and RBFP. In the latter schemes, the set of control points could conceivably be conflated with the set of keyframes, in the sense that both consist of representative subsets of the original data. Thus, RBFP-based mocap compression and reconstruction follows the slightly different workflow depicted in Figure 4.

For implementing any keyframe selection algorithm in the context of motion capture, we need to define a function for pose distance, i.e., a measure of dissimilarity.

Equation (1) defines our distance metric in terms

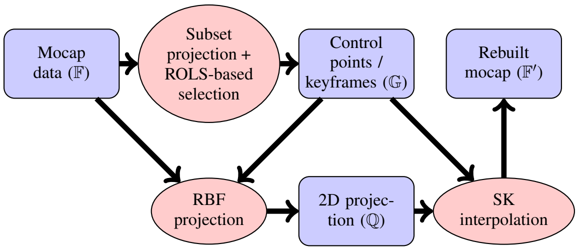


Figure 4: Workflow for mocap compression and reconstruction with spatial keyframes and RBF projection.

of local rotation matrices, where A and B are skeleton poses, R is the rotation joint set composed of matrices, $\mathrm{Tr}[\cdot]$ is the trace operator and w_r is a weight assigned to the r'th joint. In our experiments, we use this rotational pose distance definition for pose projection. The joint weight is the longest path between the joint and the furthest end effector.

$$D_q(A,B) = \sum_{r \in R} w_r \arccos\left(\frac{\mathrm{Tr}[A_r B_r^{\top}] - 1}{2}\right) \qquad (1)$$

The following multidimensional projection methods were used in our experiments. Among the linear methods, we have considered PCA (Smith, 2002), the Force approach (Tejada et al., 2003) and MDS (Cox and Cox, 2008). Among the non-linear methods, we have considered LLE (Roweis and Saul, 2000), RBFP (Amorim et al., 2014) and t-SNE (van der Maaten and Hinton, 2008). Figure 1 contains sample results obtained with all of these except RBFP. RBFP adopts a two-step projection approach using control points. In our experiments, the first step of RBFP was evaluated with the use of Force, MDS, LLE, PCA and t-SNE. Recall that RBFP prescribes the use of ROLS for keyframe selection. Figure 5 illustrates projections for the same dataset using these five RBFP variations.

4 PROJECTION OPTIMIZATION

In spatial keyframe schemes, the 2D projection of a key pose is reconstructed exactly by the back-projection algorithm, but we expect non-key poses to be reconstructed only approximately. Therefore, an important question is whether the projection of a non-key pose, as prescribed by the projection algorithm, is *optimal*, i.e., whether the back-projection of this point yields the pose with *minimum error* with respect to the original pose.

Having this in mind, we propose an optimization algorithm that will help us to find a better projection of non-key poses. This is shown in Algorithm 1, which takes as input the set of frames from the mocap ($\mathbb{F}$ in Figures 3 and 4), the subset of keyframes ($\mathbb{G}$), as well as the projection and back-projection algorithms and produces an optimized set of projected non-key poses ($\mathbb{Q}$). This algorithm implements gradient descent(Burges et al., 2005) optimization where, at each iteration, the gradient of a given function is estimated and steps in the gradient direction are taken to reach a local minimum. The original point computed by the non-optimized projection algorithm is used as a seed for the search.

An important component of the process is the estimation of the gradient at a given point. The numerical process used in our algorithm estimates the gradient around a particular 2D point by back-projecting four neighbor points within a disk of small radius and computing the error with respect to the original pose. If all points yield a bigger error than the original point, then that point is a local minimum. Otherwise, a gradient direction is computed based on the error variation. Parameters α and δ in the algorithm are typically chosen in the interval $[0,1]$ and were set to 0.5 in our experiments.

Figure 6 shows the sample projections of Figure 1 optimized with Algorithm 1. We note that the optimization tends to scatter non-key frames with respect to the non-optimized projections. Clearly, cases where greater differences exist between the optimized and original projections can be attributed to the original algorithm choosing poorer positions in the first place. We also note that the optimization algorithm can be adapted to other uses of multidimensional projection for which a back-projection is available and an error metric is defined.

5 EXPERIMENTS

The main question we face is if there is any gain in terms of quality when using spatial keyframes over traditional temporal schemes. To answer it, each compression scheme is evaluated by measuring the error between the reconstructed and the original animation, for a set of mocap files. The reconstruction quality is estimated using the error measured by Equation (1) divided by the number of frames in the mocap file and by the number of joints of the skeleton, to make this measure independent of file size or skeleton topology. We used as input data a subset of the CMU Mocap database(CMU,) with 70 files ranging in size from 129 to 1146 frames. In particular, we used files in BVH format converted for the 3DMax animation software.

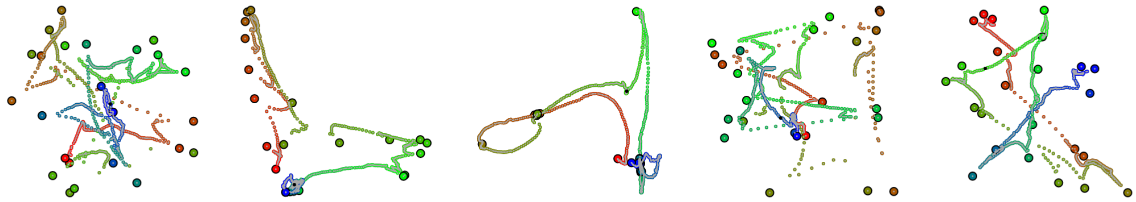


Figure 5: Results obtained by using two-step RBFP projection variants on poses of file `05_10.bvh` of the CMU Motion Capture database. The color gradient from red to green to blue is used to indicate time. Bigger dots with black border are keyframe poses (markers). The projection for the first step was obtained using the following algorithms (from left to right): Force, LLS, MDS, PCA and t-SNE.

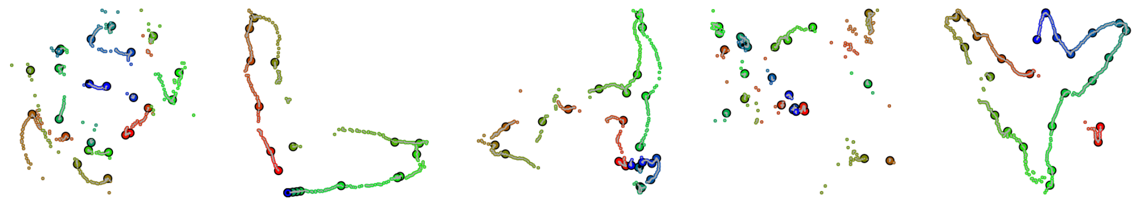


Figure 6: Optimized versions of the projections using Uniform Sampling shown in Figure 1. The color gradient from red to green to blue is used to indicate time. Bigger dots with black border are keyframe poses (markers). From left to right: Force, LLS, MDS, PCA and t-SNE.

5.1 Reconstruction Evaluation

All experiments consist of compressing mocap data and measuring the error of the reconstructed mocap with respect to the original. The compaction schemes vary according to three main aspects:

(a) The keyframe selection strategy, chosen from: PB, SCS, ROLS, and Uniform Sampling (US), which selects keyframes at regular time intervals.

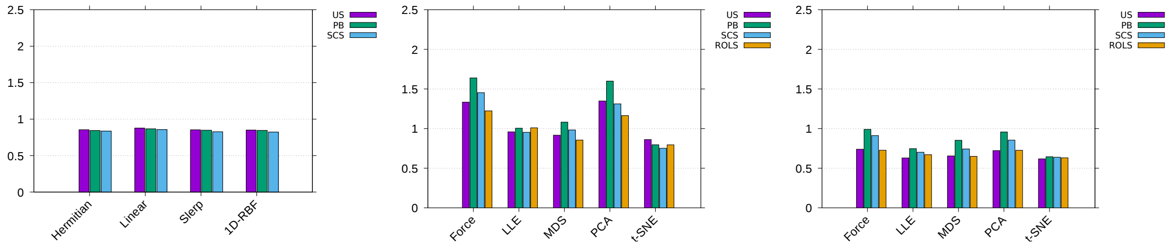
(b) The interpolation algorithm. For temporal schemes, these can be Linear or Hermitian interpolation of rotations expressed with Euler angles, or Spherical linear (Slerp) interpolation of rotations expressed as quaternions. All spatial schemes use the back-projection algorithm proposed by Igarashi et al. (see Section 3.2).

(c) For experiments using spatial keyframes we tested 5 main projection algorithms for the markers, namely: Force, MDS, LLE, PCA and t-SNE. Our LLE implementation uses the 15 nearest neighbors to reconstruct its surrounding areas. Force uses 50 iterations to reach its final projection. Experiments with t-SNE use a perplexity value of 50. The projection algorithms correspond to multidimensional projection of frames using the strategies discussed earlier. In addition to these single-step schemes, we also tested 5 RBFP-based projection schemes (see Figure 4) where the first step (keyframe projection) is performed with one of the former projection algorithms and the remaining frames are projected with RBFs.

A preliminary batch of tests was conducted in order to investigate how the compaction schemes fare with respect to the desired compaction ratio. Since this ultimately depends on the ratio between keyframes and total frames (KF ratio), we selected 9 representative animations and four compaction schemes, two temporal (Linear and Slerp) and two spatial (MDS and t-SNE), all run with SCS keyframe selection strategy, and measured the obtained error for ratios between 1 and 10%. This experiment reveals that error decreases sharply until reaching a KF ratio of about 4%, after which the error decreases at a slower rate. We used this observation to restrict further comparison tests to a KF ratio of 3%, since a smaller ratio would probably lead to bad reconstructions and a larger ratio would probably not reveal much about advantages of one scheme over another. It could be argued that rather than using a fixed KF ratio, a better comparison would maintain a desired minimum error and gauge what KF ratio would be required to attain it. Such an experimental setup, however, would be considerably more strenuous, since each scheme would have to be run several times, adjusting the KF ratio until reaching the desired error.

Figure 7 shows the average error per frame per joint for various combinations of selection and interpolation strategies at 3% KF ratio. The examination of these charts leads us to a few observations:

1. Temporal schemes as Slerp, Linear and Hermitian interpolation work well and are quite similar in terms of average error measure.



(a) Temporal schemes (b) SK schemes (c) SK schemes (2D optimized)

Figure 7: Error per frame per joint for temporal and spatial keyframe (single-step) schemes with KF ratio of 3%. Average of 70 files.

2. More sophisticate keyframe selection algorithms do not, in general, produce better results than the naive uniform sampling.
3. Spatial keyframe schemes produce good results but only if the optimized projection of (non-key) frames is used.

In particular, the overall best result was obtained with optimized t-SNE projection and uniform sampling, with an average error of 0.618 per frame per joint. On the other hand, the temporal scheme that yielded the smallest average error – 0.826 per frame per joint – was the Slerp interpolation combined with SCS keyframe selection.

The results shown in Figure 7 were produced by averaging the error over all 70 mocap files, which might hide important outliers. For a more detailed comparison, one may examine the box-plot shown in Figure 8 (see also the numeric values in Table 1)[1]. This chart omits the non-optimized spatial keyframe schemes and the Slerp-based temporal scheme. All experiments were run with keyframes selected by uniform sampling. The figure reveals that all temporal schemes exhibit a larger median than all spatial keyframe schemes. In particular, t-SNE has the smallest median and also the smallest first quartile. Isomap has the lowest minimum and LLE has the lowest third quartile. However, all except PCA show a few outliers. All spatial keyframe schemes with optimized projection show improvements with respect to temporal schemes.

Next, two-step projection schemes were evaluated with respect to their analogous one-step versions. We remind the reader that two-step methods such as LAMP and RBFP differ from their one-step counterparts in that only control points (keyframes in our case) are projected in the first step, while the remainder points use a different projector – affine maps in the case of LAMP and RBFs in the case of RBFP. Since early experiments using LAMP yielded consistently bad reconstructions, we present here only experiments with RBFP coupled with the ROLS selection strategy as suggested in (Amorim et al., 2014). Figure 9 shows a comparison chart between 1- and 2-step schemes, which indicates that RBFP yields poor results unless followed by optimization.

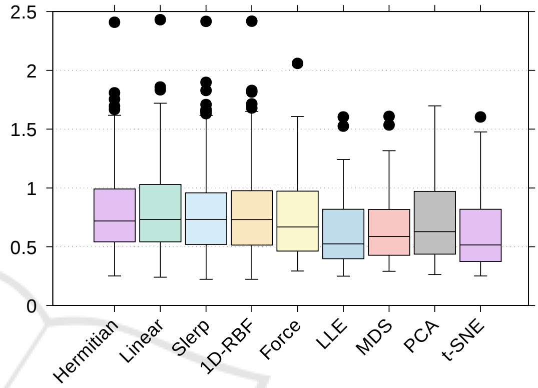


Figure 8: Error per frame per joint boxplot for temporal and spatial keyframe schemes with KF ratio of 3%. Values are available at Table 1.

Table 1: Boxplot values. W_{bot} and W_{top} are the values for bottom and top whiskers, Q_1 and Q_3 are first and third quartiles, Q_2 is the median and O is the number of outliers.

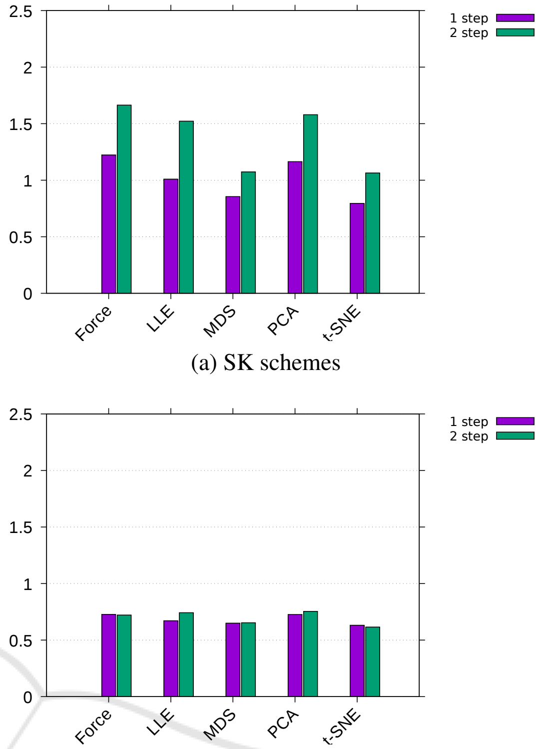
Scheme	**Boxplot values**					
	W_{bot}	Q_1	Q_2	Q_3	W_{top}	O
Hermite	0.25	0.54	0.72	1	1.62	5
Linear	0.24	0.55	0.73	1.03	1.72	3
Slerp	0.22	0.52	0.73	0.96	1.58	9
1D-RBF	0.22	0.52	0.73	0.96	1.61	8
Force	0.3	0.46	0.67	0.97	1.61	1
Isomap	0.25	0.43	0.54	0.86	1.29	4
LLE	0.25	0.4	0.53	0.81	1.24	2
MDS	0.29	0.43	0.59	0.82	1.32	2
PCA	0.26	0.44	0.63	0.97	1.7	0
t-SNE	0.25	0.39	0.52	0.81	1.48	1

[1]This boxplot chart variation draws the bottom "whisker" at the value of the lowest data point greater than $Q_1 - 1.5IQR$, where Q_1 is the first quartile and IQR is the interquartile range. Similarly, the top "whisker" is the highest data point smaller than $Q_3 + 1.5IQR$. Values lying outside the range between whiskers are considered outliers.

Algorithm 1: Gradient descent optimization for pose projection.

function GETOPTIMIZEDPROJECTION($\mathbb{F}$, $\mathbb{Q}$, $\mathbb{G}$) $\triangleright$ Optimizes projection $\mathbb{Q}$. Where $\mathbb{F}$ - frame array, $\mathbb{Q}$ - projected pose array, $\mathbb{G}$ - keyframe array.
    $\mathbb{O} \leftarrow \emptyset$
    for $i \leftarrow 1, maxtries$ **do**
        $done \leftarrow$ **true**
        for all $f_i \in \mathbb{F} \setminus \{\mathbb{G} \cup \mathbb{O}\}$ **do**
            if $gradientDescent(f_i, \mathbb{F}, \mathbb{Q}, \mathbb{G})$ **then**
                $\mathbb{O} \leftarrow \mathbb{O} \cup \{f_i\}$
                $done \leftarrow$ **false**
            end if
        end for
        if $done$ **then**
            break
        end if
    end for
end function

function GRADIENTDESCENT(f_i, $\mathbb{F}$, $\mathbb{Q}$, $\mathbb{G}$) $\triangleright$ Updates $q_i \in \mathbb{Q}$ and returns if q_i has changed. Where f_i - frame, $\mathbb{F}$ - frame set, $\mathbb{Q}$ - projected pose set, $\mathbb{G}$ - keyframe set.
    $h \leftarrow (0,0)$
    $v_x \leftarrow (1,0)$
    $v_y \leftarrow (0,1)$
    $q_i \leftarrow$ projection of f_i stored in $\mathbb{Q}$
    $q_{i+1} \leftarrow$ projection of f_{i+1} stored in $\mathbb{Q}$
    $q_{i-1} \leftarrow$ projection of f_{i-1} stored in $\mathbb{Q}$
    $r \leftarrow (\|q_i - q_{i-1}\| + \|q_i - q_{i+1}\|)/2$
    $e_o \leftarrow Err(f_i, BackProj(q_i, \mathbb{F}, \mathbb{Q}, \mathbb{G}))$
    $e_{xp} \leftarrow Err(f_i, BackProj(q_i + \delta r v_x, \mathbb{F}, \mathbb{Q}, \mathbb{G}))$
    $e_{xn} \leftarrow Err(f_i, BackProj(q_i - \delta r v_x, \mathbb{F}, \mathbb{Q}, \mathbb{G}))$
    $e_{yp} \leftarrow Err(f_i, BackProj(q_i + \delta r v_y, \mathbb{F}, \mathbb{Q}, \mathbb{G}))$
    $e_{yn} \leftarrow Err(f_i, BackProj(q_i - \delta r v_y, \mathbb{F}, \mathbb{Q}, \mathbb{G}))$
    if $(e_o > e_{xp}) \vee (e_o > e_{xn})$ **then**
        $h \leftarrow h + v_x(e_{xn} - e_{xp})$
    end if
    if $(e_o > e_{yp}) \vee (e_o > e_{yn})$ **then**
        $h \leftarrow h + v_y(e_{yn} - e_{yp})$
    end if
    if $\|h\| > 0$ **then**
        $h \leftarrow rh/\|h\|$
        $q'_i \leftarrow q_i + \alpha h$
        replace q_i by q'_i in $\mathbb{Q}$
        return true
    else
        return false
    end if
end function



(a) SK schemes

(b) SK schemes (2D optimized)

Figure 9: Error per frame per joint for ROLS keyframe selection with 1 and 2 step projection approach. KF ratio is 3%. Average of 70 files.

5.2 Compression Evaluation

Our first tests with this framework showed a poor reconstruction for in-betweens if we neglected the 2D projection for each frame and tried to reconstruct mocap by tracing the 2D controller trajectory, using only a simple interpolation between the projected keyframes. This comes from the fact that mocap data is complex and 2D projections, in particular those obtained with optimization, are not smooth but contain cusps and gaps. Thus, the easiest way to encode such trajectories is to store the coordinates of all frame projections. This is not required for temporal compression schemes which only record keyframe timestamps. Once we add more information to encode trajectories, a trade-off arises between better reconstruction quality and a less compact format.

The uncompressed data size can be stated as a function of the number of frames, as described in Equation 2, where h is the header size needed for describing the skeleton hierarchy and other constant parameters, f is the number of frames and dof the number of joints. The compressed data size for temporal schemes is described in Equation 3, where r_{kf} is the ratio between keyframes and the number of frames.

Remember that for each keyframe, we still need to keep all rotations and a timestamp or frame id to locate it in time. Also, note that the root joint data is not compressed and should be addressed by a separate scheme. Equation 4 describes the compressed data size for spatial keyframe schemes, adding two more coordinates to the format.

Considering that for our experiments we have $dof = 31$ and $r_{kf} = 3\%$, we can state that the theoretical lower bound for temporal schemes is near 6%, given that $\lim_{f\to\infty} \frac{c_t(f)}{m(f)} \approx 6.06\%$. Spatial keyframe schemes have a bigger lower bound at around 8%, given that $\lim_{f\to\infty} \frac{c_{skf}(f)}{m(f)} \approx 8.15\%$. The price of using the frame projection imposes at around 2% of lost in compression size, but is probably less if we consider a header size between 0.5% to 5% of the uncompressed file size.

$$m(f) = h + f(3dof + 3) \quad (2)$$

$$c_t(f) = h + f(r_{kf}(3dof + 1) + 3) \quad (3)$$

$$c_{skf}(f) = h + f(r_{kf}(3dof + 1) + 5) \quad (4)$$

6 LIMITATIONS AND FUTURE WORK

In this work, we have evaluated the use of spatial keyframing together with motion capture in two contexts: data visualization and compression. Our prototype handles SK-inspired animation authoring where poses can be harvested directly from the mocap and automatically associated with markers on a plane. These features, allied with a sketching interface and the visualization capabilities provided by projection certainly helps the task of creating new animations, but while the system is capable of handling more poses and longer animations than the original SK framework proposed by Igarashi et al., certain limitations of that work are still present, namely those regarding the embedding of the animation in a real scene, like the root joint translations for a skeleton moving in the scene. We plan to lift some of these restrictions with future versions of this prototype by employing some alternative scheme based on physical simulation such as (Wilke and Semwal, 2017). Also, a formal evaluation of the tool by professional animators might help us address some of its limitations.

Our investigation of the use of multidimensional projection and SK for mocap compression showed that SK generally attains smaller errors for the same amount of keyframes than temporal compression. Unfortunately, SK compression has not been shown to yield substantial gains with respect to standard temporal compression schemes in practice, mostly because in our experiments trajectories in 2D space had to be stored with no compression. Although our experimentation has been extensive, we still plan on investigating other projection algorithms, as well as using 3D projections which might yield better compression rates.

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