# Filling Long-Time Gaps of Motion Capture Data

Jan Baumann[1], Björn Krüger[2], Arno Zinke[3] and Andreas Weber[2]

[1] Fraunhofer FKIE, Wachtberg
[2] Bonn University, Institute of Computer Science II
[3] GfaR mbH, Bonn

**Abstract**

*We present a general method for data-driven filling of gaps in marker-based mocap data. The novel approach can handle challenging cases, especially if complete marker sets of multiple body parts are missing over a long period of time. Without the need for extensive preprocessing we are able to fix missing markers across different actors and motion styles.*

**Keywords:** motion capture, data cleaning, data driven methods

## 1. Introduction

Optical motion capture is the standard technique for creating realistic human motions in computer animation: Multiple cameras are used to track markers which are attached to an actor's body. Finally, 3D trajectories of the individual markers are reconstructed from the two dimensional images by triangulation techniques. Using fitting techniques, skeleton abstractions may be computed.
Although the topic of cleanup of motion capture data is a classical one and various cleaning techniques are available in commercial mocap system software, the problem is far from being solved and has obtained renewed attention in the last years [LC10]. If gaps in several markers occur for a longer period of time—a scenario quite common if closely interacting actors are captured simultaneously or interaction with the environment is essential and hence occlusion of several markers over longer time periods occur—all of the existing approaches have major limitations, especially if no previously captured motions of *the same actor* which are similar to the one to be cleaned are available. In this paper we present a general framework for data-driven filling of gaps in marker-based mocap data. The novel approach can handle challenging cases, especially if complete marker sets of multiple body parts are missing over a long period of time. Without the need for extensive preprocessing we are able to fix missing markers across different actors and motion styles. The results agree with human intuition and key features of the original input motion are greatly retained.

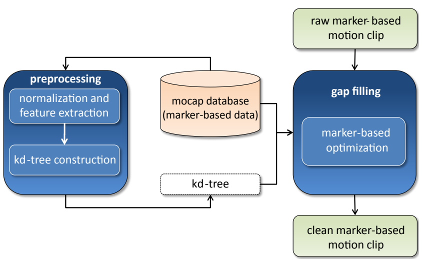


**Figure 1:** *Workflow of the proposed method.*

## 2. Overview

Our method is inspired by the solution to the *pose matching* problem presented by Krüger et al. [KTWZ10]. More specifically, we require a motion database containing motion clips comparable to the input motion. This database is the foundation of prior-based synthesis of missing markers using kernel regression.
One fundamental assumption of our method is that all poses contained in the database as well as the motion to be completed share the same marker set and that no marker mislabeling occurs.

**Preprocessing.** In a preprocessing step all mocap data from the prior-database are aligned such that poses share a common root orientation similar to Krüger et al. [KTWZ10]. Please note that this normalization requires estimating a global position and orientation which is achieved by exploit-

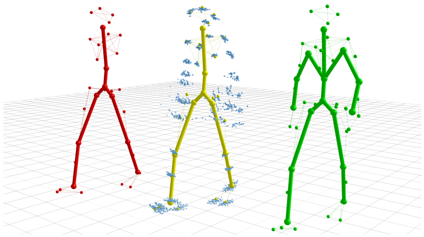

**Figure 2:** *Locomotion example in which both arms are missing for an extended time period. Our method transforms the original input motion (red) into a motion that has the missing markers reconstructed (green) by using nearest neighborhood information (blue over yellow)*

ing rigid connectivity between markers. Based on this normalized positional data we build an efficient spatial indexing structure (kd-tree). In addition, linear marker velocities as well as accelerations are stored. These quantities are required for prior-based motion synthesis.

**Synthesis of missing markers.** To fill gaps of missing markers a given motion is first normalized along the lines of the preprocessing step. Subsequently, using the kd-tree, we search for $k$ nearest neighbors for each frame (pose) that requires to be cleaned by our technique. These neighbors serve as examples for the gap filling procedure employing prior-based optimization to synthesize the positional data of missing markers. Following Tautges et al. [TZK*11] we employ energy minimization with kernel regression. Here, the objective function consists of three completely data-driven pose, motion and smoothness priors enforcing natural results that are consistent with the database samples.

$$\mathbf{x}_{\text{best}} = \underset{\mathbf{x}}{\operatorname{argmin}}(E_{\text{pose}}(\mathbf{x}) + E_{\text{motion}}(\mathbf{x}) + E_{\text{smooth}}(\mathbf{x})) \quad (1)$$

The above objective function (1) is minimized using gradient descent with respect to $\mathbf{x}$, a vector formed by the missing degrees of freedom to be synthesized. To improve efficiency, multi resolution techniques are employed. Moreover, only a subset of all frames is considered during optimization. This includes frames with highest associated costs as well as neighboring frames indirectly affecting reconstruction results through temporal derivatives occurring in motion and smoothness priors.
The whole pipeline of the proposed method is sketched in Fig. 1.

## 3. Conclusion and Future Work

We have presented a data driven method for filling large gaps in marker based mocap data. Our method works well even for large gaps from the perspective of required computational resources as well as quality of results—provided that there are sufficiently similar motions available in the prior-database. The basic mechanism can be extended to other cleaning and reconstruction tasks, such as optimal skeleton fitting and correcting marker-mislabeling. These extensions will be one topic of future work.
In contrast to previous approaches we can keep all available and cleaned motion capture data in our prior-database, and our approach scales well to huge prior-databases. The quality of our gap filling methods depends on the similarity of data contained in the prior-database and we obtain somewhat better results if motions of the performing actor of the clip to be cleaned are already contained in the prior-database. Nevertheless, our method also works quite well if such data are not available. In our approach it is possible in principle to incorporate model knowledge about skeleton constraints and contact constraints. Using a good algorithmic heuristics to estimate contact constraints from motion data—e.g. the method presented in [LCB06]—the contact information can be incorporated into the search and all defined constraints can be incorporated into the optimization procedure. We presume that such information is useful in all settings and might be crucial if for a gap-filling the information of body segments such as lower-body parts or upper body parts only are considered. Such restrictions to body parts allow an extension of the notion of "similar motion" to ones being similar for body parts only.

In our future work we will explore the algorithmic techniques and will perform empirical investigations for incremental extension of the prior-databases: cleaned motion clips can be incrementally added to the prior-database potentially allowing a step-wise extension of the expressibility of the prior-data base. With such extensions motions which could not be handled by a original prior-database might become tractable by the newly added clips.

Building a practical tool allowing the use and re-use of a ever growing corpus of motion capture data obtained in more and more complex capture scenarios is the ultimate goal of our research.

## References


[KTWZ10] Krüger B., Tautges J., Weber A., Zinke A.: Fast local and global similarity searches in large motion capture databases. In *Proceedings of the 2010 ACM SIGGRAPH/Eurographics Symposium on Computer Animation* (Aire-la-Ville, Switzerland, Switzerland, July 2010), SCA '10, Eurographics Association, pp. 1–10. 1

[LC10] Lou H., Chai J.: Example-based human motion denoising. *IEEE Transactions on Visualization and Computer Graphics 16* (2010), 870–879. 1

[LCB06] Le Callennec B., Boulic R.: Robust kinematic constraint detection for motion data. In *Proceedings of ACM SIGGRAPH / Eurographics Symposium on Computer Animation* (sept 2006). 2

[TZK*11] Tautges J., Zinke A., Krüger B., Baumann J., Weber A., Helten T., Müller M., Seidel H.-P., Eberhardt B.: Motion reconstruction using sparse accelerometer data. *ACM Trans. Graph. 30* (May 2011), 18:1–18:12. 2