# Approaches and Challenges in the Visual-interactive Comparison of Human Motion Data

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Abstract: Many analysis goals involving human motion capture (MoCap) data require the comparison of motion patterns. Pioneer works in visual analytics recently recognized visual comparison as substantial for visual-interactive analysis. This work reflects the design space for visual-interactive systems facilitating the visual comparison of human MoCap data, and presents a taxonomy comprising three primary factors, following the general visual analytics process: algorithmic models, visualizations for motion comparison, and back propagation of user feedback. Based on a literature review, relevant visual comparison approaches are discussed. We outline remaining challenges and inspiring works on MoCap data, information visualization, and visual analytics.

## 1 INTRODUCTION

Data has long become one of the greatest scientific assets. Almost any application field gathers huge amounts of data, e.g., to conduct data-driven research. In a variety of research and application fields such as medicine, sports, or animation data recorded of human motion is collected and stored and made publicly available. This *human motion capture (MoCap) data* can be regarded as an instance of multivariate time series consisting of many numeric attributes depending on time. A variety of systems and devices has become available for recording MoCap data, e.g., for recording motion by tracking body positions optically in a markered (Peak, 2005) or marker-less setup (Zhang, 2012), as well as by tracking accelerations, angular velocities (Roetenberg et al., 2009), and muscle activation (De Luca, 2003). All of these will be referred to as MoCap data, representing unique characteristics of human movement with respect to specific semantics and their analysis applications.

Additionally, based on the different sources of MoCap data, there are frequently applied established strategies to derive representations of the primary data resulting in deduced or secondary data. One of the most often applied strategies is the extraction of features. Extending the primary data the MoCap analysis domains have created specific methods and techniques focused on exposing and extracting as much of the semantics as possible. Representative of these are descriptors and segmentation methods that typically exploit both temporal and spatial information.

The increase of both primary and secondary MoCap data has created a need for efficient methods for processing and analysis. Typical analytical fields are data mining, machine learning and information retrieval. Recently, pioneer approaches in the visual-interactive analysis of MoCap data have emerged in the fields of information visualization and visual analytics (Bernard et al., 2013; Ragan et al., 2016; Wilhelm et al., 2015; Bernard et al., 2016). These initial approaches clearly indicate that visualization can be beneficial for analyzing MoCap data by emphasizing cognition and generating insight. In particular, the techniques used to *visually compare* the data proved beneficial for supporting envisioned analysis goals and tasks.

Obviously, these inspiring approaches provide only initial assessment of what visual comparison can be used to ease the analysis of MoCap data. Many data mining, machine learning and retrieval approaches can be enhanced with visual comparison techniques to ‘open the black box’. Examples are the validation of model results or even the integration of visual comparison techniques within the analytical workflow.

Altogether, visual comparison can support tradi-



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Table 1: Overview of the analytical tasks that benefit from visual comparison.

| Task | References |
|---|---|
| **Retrieval** | (Müller, 2007; Lew et al., 2006) |
| **Tracking** | (Moeslund et al., 2006) |
| **Cleansing** | (Gschwandtner et al., 2012) |
| **Wrangling** | (Kandel et al., 2011) |
| **Reconstruction** | (Hu et al., 2004) |
| **Similarity search** | (Krüger et al., 2010) |
| **Feature analysis** | (Mörchen, 2006) |
| **Descriptor analysis** | (Keogh and Kasetty, 2003) |
| **Pattern/anomaly detection** | (Sakurai et al., 2015) |
| **Rule discovery** | (Mörchen, 2006) |
| **Recognition** | (Moeslund et al., 2006) |
| **Classification** | (Müller and Röder, 2006) |
| **Clustering** | (Warren Liao, 2005) |
| **Segmentation** | (Fu, 2011) |
| **Prediction** | (Mörchen, 2006) |
| **Monitoring** | (Lin et al., 2004) |
| **Exploratory Search** | (Bernard, 2015) |

tional analytical tasks — such as listed in Table 1 — that benefit from visual comparison.

It can also be assumed that visual comparison of MoCap data would further advance the analysis of human motion in many applications. Physicians can express, combine, and validate their observations of human movement, e.g., towards the quantification of observed progress in rehabilitation, by relying on MoCap data. Visual comparison can also help identify and prevent patient behavior leading to injury and deterioration. In professional sports, trainers would be able to assess the physical fitness of sportsmen by visually comparing MoCap data of individuals to others in the team or against reference athletes. In exploratory applications, experts may seek differences between individuals or groups to categorize, organize, or structure large unknown data sets. In summary, visual comparison can facilitate various analysis goals and tasks involving human motion patterns. Hence, a variety of experts in a number of domains can be supported in performing their analysis tasks, e.g. in data-driven research to generate and validate hypotheses.

However, supporting the visual comparison of MoCap data is not an easy task. At a glance, we identify three primary challenges aggravating the design of visual-interactive analysis systems. The first challenge comes with the classical problem of assembling multiple *algorithmic models* in the right order with the right parameters. As an upstream task in the process, the input data need to be cleansed in order to meet the quality requirements of algorithms. In addition, adequate features and similarity measures need to be defined. At heart of the first problem is the definition of pattern abstraction algorithms to cope with the complexity of the temporal domain. The second challenge refers to the characterization of appropriate visualization designs to support *visual comparison*. At least three aspects need to be taken into consideration. MoCap patterns can be compared at different levels of granularity including single dimensions (features), single patterns (elementary level), and groups of pattern (synoptic level) (Andrienko and Andrienko, 2006). In addition, we distinguish between the comparison of a single object at different times (e.g., stages of a recovery process) and the comparison between subjects or groups of subjects. Finally, the distinction between comparing original MoCap patterns and derivatives of patterns (delta-visualization) is an issue by itself. The third primary challenge is associated with the matter of integrating a *feedback loop*, i.e., facilitating a 'human-in-the-loop' process, allowing the adaption and improvement of analytical models and outcomes. Providing meaningful interaction designs is one part of this challenge. Back propagation of feedback triggering algorithms to adapt results towards users' information needs is another.

Based on a review of related works in the fields of human MoCap analysis, information visualization, and visual analytics, we contribute an overview of approaches and challenges in the visual-interactive comparison of human MoCap data. To this end, we characterize the problem space according to three main factors reflecting the algorithmic workflow of the visual analytics process (Keim et al., 2010). At a glance, this space covers challenges of algorithmic models, designing comparative visualizations, and closing the feedback loop. For each of the three factors, we discuss a series of related technical obstacles and survey related works as far as proposed yet. The characterization of the problem space can be used as a light-weight taxonomy for the design of visual-interactive analysis approaches using visual comparison as a means to support analysis goals and tasks.

# 2 APPROACHES AND CHALLENGES

This section provides an overview of approaches and remaining challenges in the visual comparison of MoCap data. The problem space is structured by three prior factors with interactions highlighted in Figure 1.

## 2.1 Algorithmic Models

### 2.1.1 Pre-Processing

Techniques employed for cleansing, tracking and wrangling ensure that data are in a state they can be used for further processing. The works of Gschwandtner et al. (Gschwandtner et al., 2012) and Kandel et al. (Kandel et al., 2011) provide taxonomies of 'dirty'

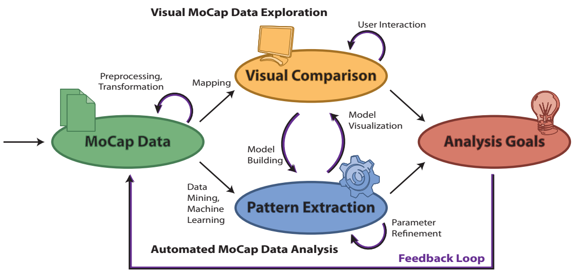


Figure 1: Interplay between MoCap data, extracted patterns, and visual pattern comparison, adopted from the visual analytics process (Keim et al., 2010). The feedback loop can trigger data transformations, model building, model visualization, and parameter refinement.

time series and cleansing strategies, Bernard et al. present a visual-interactive tool for preprocessing univariate time series (Bernard et al., 2012a). Specifically for MoCap data, the survey of Moeslund et al. (Moeslund et al., 2006) discusses advances in the state of the art in pre-processing records of articulated motion. MoCap data often have to undergo further specific pre-processing steps such as re-sampling and filtering in order to meet the quality requirements of downstream algorithms. As MoCap data carry unique semantic information, the pre-processing has to ensure this structure is preserved (cf. Bruderlin and Williams (Bruderlin and Williams, 1995)). The general role of *descriptors* in mining time series data is discussed in the survey of Keogh and Kassety (Keogh and Kasetty, 2003), particularly, with a focus on the biases caused by implementation and experimental data. MoCap data encode a spectrum of semantic information ranging from task-oriented (gross sensory) to gestures and communication (fine-motor). The choice of meaningful descriptors for different full-body setups is one challenging aspect (Tautges et al., 2011). As the representation of fine motor movement in associated applications and use cases is a highly specific and complex task, there is yet no general solution for the design of descriptors and features. Several works discuss how to face the challenge of information and semantics preservation when defining feature spaces for motion data (Müller and Röder, 2006; Krüger, 2012).

#### 2.1.2 Pattern Extraction

Extraction of patterns from time series data is a topic that has been addressed in a variety of contexts. The explosion of interest in time series *segmentation* and mining has raised many interesting research topics from the representation of input data to clustering, and classification algorithms. An earlier overview of advances in the analysis of time series data bases is found in the survey of Keogh et al. (Keogh et al., 2004). Motion data segmentation has since seen rapid development, both in the context of detecting activities and detecting motion primitives (Barbič et al., 2004; Zhou et al., 2013; Wang et al., 2015; Vögele et al., 2014). As a recent development, visual-interactive toolkits applying a variety of general segmentation algorithms on MoCap data have been proposed (Bernard et al., 2016). Identification of cyclic and periodic behavior is of specific interest in processing MoCap data for the repetitive nature of human motion. This is reflected by the findings of Wang et al. and Vögele et al. (Wang et al., 2015; Vögele et al., 2014). Segmentation tasks are typically embedded in the more general analysis task of investigating MoCap *patterns*. Generally, relating sub-sequences of time series to one another allows for outlier and anomaly detection, as well as for frequent pattern analysis. An overview of the most important tools in pattern recognition is found in the Sakurai et al. (Sakurai et al., 2015). For motion data, the analysis of frequent patterns and anomalies comprises processes such as detection, segmentation, recognition, classification and identification. Surveys on pattern and anomaly detection are found in the works of Wang et al. (Wang et al., 2003) and Chen et al. (Chen et al., 2013). The analysis of time series data depends on the *similarity measures* employed, for a review see, e.g., the work of Aghabozorgi et al. (Aghabozorgi et al., 2015). The choice of adequate similarity measures for MoCap data is discussed in detail in the works of Krüger et al. (Krüger et al., 2010; Krüger et al., 2015). In this connection the concept of self-similarity has proven to be beneficial. However, it remains a challenge to integrate representations of self-similarity into visual-interactive systems as a means of visual comparison.

### 2.2 Visualizations for Motion Comparison

We survey approaches and challenges related to the visualization of patterns to be compared. The three issues rely on the granularity of the patterns, the scope of users in their application, as well as on the class of visual comparison technique.

#### 2.2.1 Different Levels of Granularity

The visual comparison of MoCap patterns basically comes with three different levels of granularity, i.e., features, single objects, and groups of objects.

The visual comparison of *features* (dimensions) is a popular field of research in general. More specifically, techniques for the visual comparison of univari-

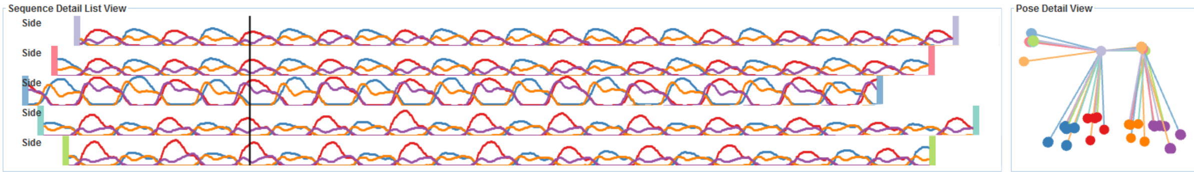


Figure 2: Visual comparison of horse gaits (Wilhelm et al., 2015). Four features of hoofes are represented with time series visualizations (red, blue, orange, purple curves). Moreover, the features of six individual horses visualized in a line-based visualization. User interaction allows the temporal synchronization and visual comparison of feature progressions.

ate time series can be seen as an instance of comparing individual features. We refer to the book of Aigner et al. for an overview of time series analysis approaches including visual comparison tasks (Aigner et al., 2011). The LiveRac approach supports the visual comparison of multivariate time series features (McLachlan et al., 2008), the challenge of visual scalability is solved by prioritizing features depending on their interestingness (McLachlan et al., 2008). The creation of trajectories is one technique applied for the visual comparison of features or sets of features (Krüger et al., 2010; Tautges et al., 2011). As an alternative multiple linecharts can be used to represent and compare multiple features (Bernard et al., 2016). However, one remaining problem of this class of techniques is the pure number of dimensions causing visual overplotting. This problem can be addressed by supporting the selection of interesting feature subsets, as provided in the FuryExporer approach where users can select features reflecting horse body positions for a detailed comparison (Wilhelm et al., 2015). An example is depicted in Figure 2 showing four selected hoofes (red, blue, orange, purple). It becomes apparent that the visual comparison of features needs to address at least three degrees of freedom: temporal offset, feature normalization, and motion speed.

The visual comparison of individual MoCap *patterns* can support elementary (Andrienko and Andrienko, 2006) analysis tasks, i.e., the comparison of single or several individual objects. In general a variety of approaches exist supporting the comparison of patterns, e.g., for analysts seeking periodic behavior, frequent patterns, or anomalies. Again, we refer to the book of Aigner et al. for an overview of approaches related to general time series data (Aigner et al., 2011). For MoCap data we refer to a motion pattern as a small (sub-)sequence worth to be analyzed as an individual data object. Since motion patterns can have different characteristics with respect to the temporal and the value domain one challenge for the visual comparison is emphasizing aspects that contribute to the differentiation of patterns while reducing less important information for the visual comparison. One visual approach for the comparison of MoCap segmentation results preserves the length of the patterns (here: segments) while abstracting the multivariate value domain to similarity-preserving colors (Bernard et al., 2016). Other approaches abstract from the temporal domain by projecting the multivariate MoCap data into 2D, yielding path metaphors allowing the visual comparison of patterns (Hu et al., 2010; Bernard et al., 2012b; Wilhelm et al., 2015), see, e.g., Figure 4. In these cases patterns may not even be explicit, but may be identified by analyzing path distributions in the 2D output space. One class of visual comparison approaches considering both the temporal and the value domain is based on self-similarity, often represented with matrix visualizations (Vögele et al., 2014), see Figure 3.

The visual comparison of *groups of patterns* supports analysis tasks at a synoptic (Andrienko and Andrienko, 2006) level. Presumed that upstream challenges in extracting patterns are addressed, challenges exist in visualizing clusters (bundles) of patterns, ideally including information about their variance. Lin et al. avoid this problem by transforming time series into an alphabet of symbols, yet leading to a visually scalable solution (Lin et al., 2005). Another way to represent the variance of patterns is to apply visual metaphors known from uncertainty visualization (Gschwandtner et al., 2016). Examples for MoCap patterns are slope visualizations (Min and Chai, 2012) or bundling techniques for clusters of human poses (Bernard et al., 2013), see Figure 5. In addition, projection-based techniques reveal variances in the value domain of motion patterns by spatial distributions of path metaphors in 2D (Hu et al., 2010; Bernard et al., 2012b; Wilhelm et al., 2015).

#### 2.2.2 Scope of Compared Objects

The review of related works in MoCap analysis revealed that approaches can be differentiated in within-subject and between-subject analyses, see Figure 6. Within-subject analyses focus on individual subjects that are observed over absolute time. Between-subject analyses often abstract from absolute time and compare different subjects or groups of subjects. From a visualization point of view taking the absolute time

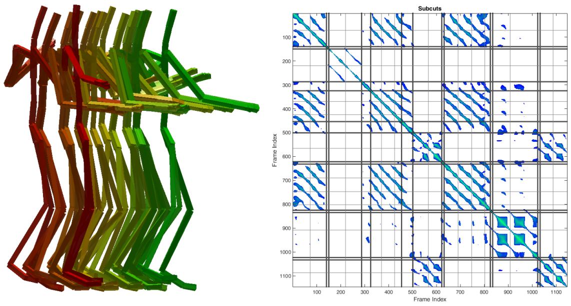

Figure 3: Examples for the visual comparison of a series of poses. Left: the 2.5D visualization represents the performed motion, overplotting remains a challenge. Right: self-similairty matrix showing periodic motion over 1,150 tracked frames (Vögele et al., 2014; Krüger et al., 2015).

into account causes additional challenges. Representatives of such *within-subject scenarios* make use of absolute time are found in rehabilitation and physical performance improvement (Zhou and Hu, 2008; Payton and Bartlett, 2007). Many exploratory data analysis scenarios are based on between-subject comparison. Exploration may also reveal interesting individuals to be analyzed in a within-subject scenario.

#### 2.2.3 Comparing Data or Derivates

The third challenge in the scope of designing visualizations for the comparison of MoCap data refers to the comparison concept. According to Gleicher et al. (Gleicher et al., 2011) visual comparison techniques in general can be differentiated into three classes. First, the class of *juxtaposed* visualizations showing different objects side-by-side (see, e.g., Figure 4). Second, the class of *superimposed* visualizations where multiple layers are used to represent multiple objects (see, e.g., bundles in Figure 5). Both classes use the original data to support the visual comparison task. In contrast, the third class of techniques is referred to as *explicit encoding* showing not original data but differences between objects or details about their (co-)relations. A classical example from time series analysis combining superposition and juxtaposition is the calender view approach presented by van Wijk et al. (Van Wijk and Van Selow, 1999) showing differences between clusters of daily time series patterns. A frequently applied technique based on juxtaposition is showing small multiples of a given type of object side-by-side, e.g, in the context of univariate time series patterns (Fuchs et al., 2013). Explicit encoding of differences can, e.g., be achieved with glyphs, allowing the visual representation of a set of abstract data attributes in a compact and representative way (Borgo et al., 2013). Considering MoCap data, superimposed techniques exist for the visual comparison of clusters of human poses (Bernard et al., 2013; Jang et al., 2016), allowing the analysis of variances, i.e. style variations of individual poses. Similarly, multiple cluster visualizations can be used to compare patterns in a juxtaposed way, e.g. aligned with respect to the high-dimensional structure of the data, structured as a result of projection algorithms (Bernard et al., 2013) or sequence visualizations (Jang et al., 2016). One specific characteristics of MoCap data is the visualization of directions and accelerations of human poses to represent the temporal domain (Tautges, 2012). While this property adds to the challenge of comparing motion patterns visually, it can be seen as a type of explicit encoding.

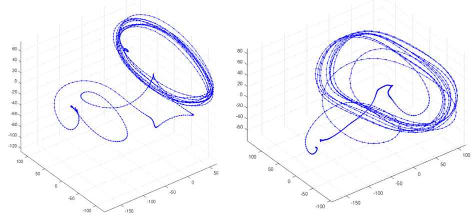

Figure 4: Visual comparison of two individuals performing a motion class (Krüger et al., 2015). Dimension reduction is applied to make the highdimensional spatial domain visually comparable. This type of vector space representation comes with the cost of loosing semantical information.

### 2.3 Integrating the Feedback Loop

Any user interaction can be considered as potential feedback for the system. Interaction in visual analysis systems enables users to adapt the visual representation, the visual encoding of data, but also algorithmic models to improve analysis results, successively. We discuss challenges regarding user interaction in combination with MoCap data analysis, an overview of interactive visual analysis approaches for multifaceted scientific data in general is, e.g., presented by Kehrer and Hauser (Kehrer and Hauser, 2013).

#### 2.3.1 Synchronization of MoCap Patterns

Apart from general interaction designs MoCap data analysis can benefit from techniques supporting the *interactive synchronization of MoCap patterns* with the goal to optimize the visual representation of individual temporal domains for the visual comparison. In this way, users can focus on specific features, patterns, or groups of patterns that are particularly interesting for visual comparison. One example where interaction is used to synchronize MoCap patterns is provided with the FuryExplorer approach (Wilhelm

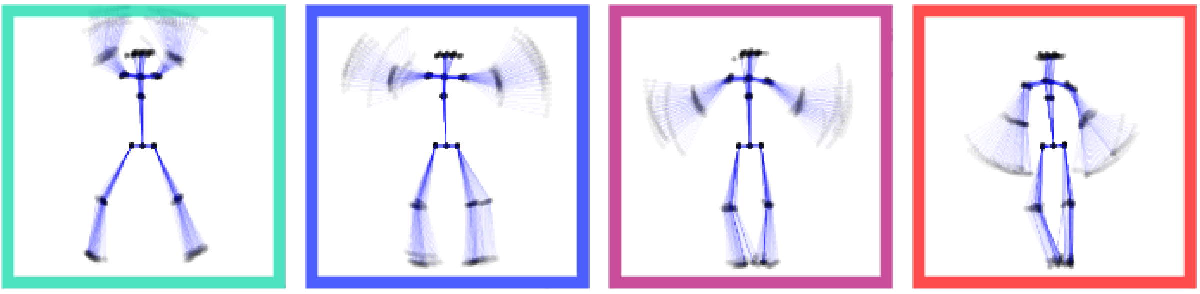

Figure 5: Visual comparison of groups of MoCap patterns (Bernard et al., 2013). In the example the result of clustered poses is compared visually. The hip was used to align different poses at center of the visualization, i.e., to foster visual comparison in an intuitive way. The example indicates that color can be an effective means to communicate orderdness or even similarity.

et al., 2015). To improve synchronization, user interaction applies affine transformations on single MoCap patterns which can visually be compared in a juxtaposed horizontal arrangement. One associated challenge refers to the tedious process of aligning individual MoCap patterns, leading to the research question on how to generalize local synchronization results for the entire data set. One approach borrowed from time series analysis is the idea of identifying local points of interest (Schreck et al., 2012). These points of interest can be a basis to automate pattern synchronization tasks, similar to approaches matching point clouds in the visual computing domain (Goesele et al., 2010).

#### 2.3.2 Histories of User Interaction

One primary challenge associated with the use of interaction is to provide the *history of user interaction*, which represents one type of provenance information. While providing provenance information has come to attention in information visualization (Ragan et al., 2016) in general, it has hardly been considered for the visual analysis of MoCap data. Challenges are the visual representation of interaction states, as well as the identification of 'interaction mile stones' (cf. (Ragan et al., 2016)). Depending on the granularity of the analysis (cf. Section 2.2.1) limitations in the available display space need to be considered.

#### 2.3.3 Back Propagation of User Feedback

A core principle of visual analytics is to support user interactions that trigger algorithmic models for result adjustment and successive improvement. Being able to compare different analytical results in a visual way is key to conduct effective analysis approaches. The visual comparison of data objects and clusters was exploited in various visual analytics approaches including multiple classes of algorithms. For MoCap data feedback loops were implemented for clustering and projection (Bernard et al., 2013), visual abstraction and aggregation (Jang et al., 2016), and segmentation (Bernard et al., 2016). However, the majority of algorithmic models and workflows in the MoCap data analysis domain is grounded on 'blackbox' approaches, which can be enhanced by putting the user in the loop. The specificity of algorithms and the complexity of workflows may pose additional challenges for MoCap data (cf. Section 2.1). Example models that could be accessed by the feedback loop are algorithms for data cleansing, normalization, feature selection, descriptor choice, and similarity search. In addition, active learning approaches and other concepts based on machine learning could be integrated to capture user feedback and improve the analytical outcome. In summary, coping with the huge design space defined by the different algorithmic models by including the back propagation of user feedback remains subject of future work.

## 3 CONCLUSION

In this work, we presented an overview of approaches and challenges in the visual-interactive comparison of human motion capture data. The characterization of the problem space grounded on three essential factors, i. e., algorithmic models, designing comparative visualizations, and enabling analytical feedback loops. For each of the three factors, we identified a series of challenges and surveyed related approaches concerned with each of them. We identified various gaps in scientific literature regarding the problem space and associated challenges. Pursuing collaborative approaches can be one way to mitigate these gaps. Specialists involved in the analysis of human motion capture data could contribute their domain knowledge and elaborate novel approaches together with experts in information visualization and visual analytics. While this type of collaboration can contribute to answering basic research questions, the involvement of users working on real-world problems

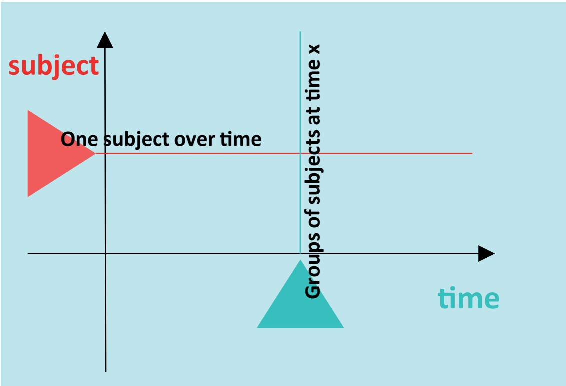


Figure 6: Two abstract analysis tasks often applied in the analysis of human motion. Comparison of a single subject at different times and multiple subjects at a given time.

would lead to relevant and useful applications.

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