

MoComp: A Tool for Comparative Visualization between Takes of Motion Capture Data

Carl Malmstrom, Yaying Zhang, Philippe Pasquier, Thecla Schiphorst, Lyn Bartram

School of Interactive Arts and Technology, Simon Fraser University

102 Avenue, Surrey, British Columbia, Canada

{cmalmstr, yayingz, philippe_pasquier, thecla, lyn}@sfu.ca

ABSTRACT

We present MoComp, an interactive visualization tool that allows users to identify and understand differences in motion between two takes of motion capture data. In MoComp, the body part position and motion is visualized focusing on angles of the joints making up each body part. This makes the tool useful for between-take and even between-subject comparison of particular movements since the angle data is independent of the size of the captured subject.

Author Keywords

Movement Visualization; Comparative Visualization; Motion Capture

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation: Miscellaneous

INTRODUCTION

The motion of living things is a fascinating phenomenon that only recently has been possible to analyze methodically in 3D with the advent of motion tracking and motion capture technology. This technological advance has highlighted the richness and nuances of motion that is essentially what makes it natural and alive.

The study of human motion and its characteristics has been a growing research area as motion capture technology has become increasingly prevalent and accessible. Much of the research is focused on the identification and characterization of motion and its shape, effort and even emotion [2, 3, 4, 5]. There is also research being conducted on how human motion best is visualized in more abstract ways than through video clips or animated skeletons [6, 7, 8].

However, in applications and tools using motion capture data we see an emphasis on the comparative rather than the characterizing or descriptive nature [7, 9]. By comparing two motion capture sequences some insight and understanding of

a movement can be drawn without advanced analysis of the high dimensional and complex dataset. This allows such tools to be effective in contexts outside the research area of motion analysis.

There is a widespread and established practice in education and training where subjects are taught a procedure by demonstration and mimicking. These situations are for example found in sports or performing arts, both of which are areas where motion capture is also applicable and meaningful to use. But the complex and interconnected nature of the human body and the movement of its parts makes interpretation and isolation of singular joints and actions difficult in real-time, and to do it throughout a sequence of movement is an even more challenging task. This issue is at the heart of this paper.

After glancing over the current state of research in the field we will formulate a research question for the creation of a visualization tool within this space. By detailing the ensuing design process and implementation we provide a thorough introduction of MoComp, a comparative visualization tool for takes of motion capture data. We proceed by describing the final prototype and summarize a small usage study conducted to evaluate its effectiveness before concluding with our own analysis of the prototype underpinned with the results from the usage study.

BACKGROUND AND RELATED WORK

Motion Capture

Outside the research community, motion capture was adopted early by the motion picture, game and animation industries [11]. The use case here is to capture the movement of real actors to make animated characters appear more natural and alive [10, 11, 12]. This capturing of dedicated sequences for short term use resulted in proprietary data structures and limited sharing, something that is still an issue within the field [10].

There has been attempts to improve the situation and the number of freely-available motion capture takes is increasing [13]. An example of this is the free and open source database MoDa [13], described further in the next section, which we are taking advantage of within this project.

Fundamentally, motion capture data is time-series data for a set of points and their positions in 3D-space. The points are derived from markers placed at different parts of a body, and have interrelationships springing from the structure of that

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MOCO'16, July 05-06, 2016, Thessaloniki, GA, Greece

©2016 ACM. ISBN 978-1-4503-4307-7/16/07 \$15.00

DOI: <http://dx.doi.org/10.1145/2948910.2948932>

body. These relationships can be used when storing the data to create a hierarchical structure where one point is used as a root to which all the other points relate directly or indirectly through the hierarchy. The collection of points makes up the skeletal representation of the captured subject. There is no consensus on the file format or order of the hierarchical structure in the skeleton, which hinders parsing of data from multiple sources [10].

MoVa and MoDa

MoDa, MoVa and MoTate are recent efforts within the motion data analysis field made by the Moving Stories laboratory at Simon Fraser University [1, 13]. MoDa is a freely-accessible and open source database for storing, structuring and accessing motion capture takes. The aim of that project was to provide a framework to encourage and distribute well-organized motion capture data for the research community [13].

MoVa is an open-source web-application used to visualize and analyze motion capture takes through parsing of data and subsequently displaying animated and static skeletons in conjunction with basic visualizations for a large set of extracted features. Finally, MoTate is an extension of MoVa that allows researchers and motion analysts to annotate the takes in a structured way [1].

Feature Extraction

The aforementioned richness of motion capture data incorporates a large number of features possible to extract from it. Some of them are possible to deduce by applying well-defined algorithms on the dataset whereas others are more indefinite and might require manual human annotation. In the previously cited MoVa application there are, for example, algorithms to expand the dataset with kinematic and Laban effort data of the motion [5].

In their venture to construct a virtual reality application for ballet dance training Kyan et al. [9] transforms rather than expands the dataset to extract features from it. To reach their intent to provide real-time feedback on dance poses they extract and make use of angles of limbs rather than spatial X, Y and Z positions. They argue that this approach eliminates invariance caused by subject size and motion capture device position [9]. By defining an upper and lower coordinate system within the subjects body the spatial position data of joints can be projected onto planes defined by this coordinate system and their relative angles can be derived. The coordinate systems are redefined in each capture frame and are based upon the relative positions of shoulders, spine and hips. Using two relative angles the position of each joint is well-defined in three dimensional space and in Kyan et al.s application they are used for real-time comparison between the pose of a performing subject and a previously captured professional trainer.

Comparative Visualization

There are visualization techniques developed specifically for comparative data analysis in various fields of research. Some examples are Busking et al.s [14] design of an image-based tool for comparing surfaces, van Pelt et al.s [15] system for comparing blood vessel flows using expandable glyphs and

Zhang et al.s [16] glyph-based visualization for comparing diffusion tensor fields. However, as they are all developed for a specific kind of data and use case, the techniques presented can mostly serve as an inspiration when considering comparative visualization in a non-related field.

Visualizing Movement

The basic method to visualize motion data is by animating a polygonal or skeletal representation by applying the translations and rotations of each joint in the data to the represented joint in a virtual 3D space on the screen. This approach is a natural derivation of the complexity and origin of the data, and, hardly surprising, its effective for communicating the shape and character of a movement [17]. The drawbacks are inexact or impossible deduction of values from data points, a difficulty of summative or comparative analysis because of this and the cognitive strain put on the user to remember poses over time if the temporal dimension is animated.

When instead looking to visualize motion data using established visualization idioms and techniques one runs a high risk of overplotting and overloading the users cognitive abilities because of the complexity and dimensionality of the typical dataset. Therefore the reduction and abstraction of motion data is a common topic, especially when the data is temporal.

An example comes from Alexiadis and Daras [7] who transform the three dimensional spatial data of each joint to a quaternionic signal to treat the space dimensions collectively. After doing this they can implement fairly basic line graphs to encode the abstracted dataset. However, abstraction distances the data trends and values possible to deduce from the visualization so that their consequence on the actual pose and shape of motion as we are used to experience it, in real-time 3D space or relative to our own body, is muddled.

RESEARCH QUESTION

We imagine more applications of motion tracking data analysis can be discovered by focusing on the post-capture comparison of movement sequences rather than the isolated study of a single sequence or the real-time comparison of motion to a previously captured sequence or pose. Such applications might include movement learning and perfection by imitation; an example would be an aspiring amateur improving their skill in a sport, martial art or dance by trying to imitate a professional.

While analytical measure of similarity and differences would be very useful in the future, our intent is to approach this from a visualization perspective. In order for a user to have the possibility to compare poses, timing and variables such as speed or acceleration of isolated joints this information has to be presented comparatively for both sequences in one comprehensive view.

The aim of this project was to enable a meaningful and accessible way to extract and comprehend differences in movement by developing a visualization tool. The prototype solution presented in this paper is based on the existing framework around MoVa, constructed as a component extending MoVa.

DESIGN PROCESS

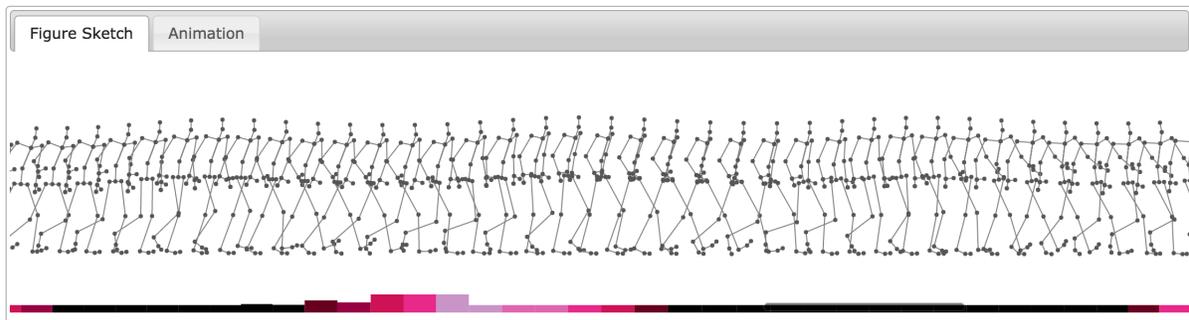


Figure 1. MoVa

Context of Use

Because the research question is centered on an extension of possible applications rather than trying to cater to a specific use case and user we have the freedom to discuss and define the potential users to design for. We decide to approach this by making the visualization usable to a broad spectrum of users by adhering to established visualization idioms and keeping a close relationship between the data and the real-world. Rather than specializing to a specific use-case and user we design to minimize the users excluded so that suitable use-cases can emerge through the exploration of the prototype by users of different backgrounds.

Abstraction and Reduction of the Dataset

Intending to design comprehensible and usable visualizations out of sizable and high-dimensional motion capture datasets prompts a decision on abstraction and reduction. An initial reduction, or rather specification, of the data to study is deemed necessary to allow users to specify the time period of the motion takes at hand to study.

Because of the intended use of the prototype there was an emphasis to keep the dataset relatable to a users own body through this abstraction and reduction, which puts advanced algorithms that severely transforms the data out of the question. We decided to make use of body-dependent angles of the joints because this makes sense in the real-world while reducing the dimensionality of the dataset from representing three dimensional spatial position using the three room dimensions to using two angles. We argue that angles of a joint, i.e. the knee, in two perspectives is intelligible and relatable to ones own body for a majority of users. This abstraction has the added benefit of negating the differences in the data caused by the recorded subjects size, which makes the visualization effective for a larger number of scenarios.

The size of the dataset makes it challenging to encode into a single visualization without overplotting or overloading users cognitive resources. To overcome this we reduce the number of joints to treat by focusing on a single body part at a time. The main argument is that the isolation of a body part enhances the possibility to truthfully study it without interference of the rest of the body. We also imagine a suite of applications where the main interest will lie in the movement of a single body part, for example if trying to improve your ping pong serve. Through this reduction we avoid overloading the

cognitive resources of the user and allow for the visualization to be comprehensible.

In scenarios where all body parts are of interest the user is forced to study one at a time, and can hopefully deduce the sought conclusions from each separately and in conjunction.

Only looking at angles of joints might be a simplification of the data that eliminates some of the nuances that are essential to the motion dynamics. Therefore we decide to extend the feature set to also include angular speed and angular acceleration to allow for a more rich analysis.

Body-based Perspectives

Through the abstraction of the data we are left with angles that convey the positioning of joints. As the movement encompasses three dimensional space two angles are necessary to provide well-defined positions. So facing the question of which planes to calculate angles in we again put consistent emphasis on the relatability of the visualization to the real-world and users own bodies. This resolution have us arrive at a decision of using perspectives looking at the captured body from the back and from the side of the body itself. This means that the movement of the body through space is set aside to provide a clear view of the relative movement of body parts in the body.

Alternatives using the same idea are a front and floor or ceiling perspective, but these are not equally relatable. One might argue that the floor or ceiling perspective is useful but our belief is that humans are more used to, and therefore better at, studying movement of themselves and others from a perspective easily attainable in real-life by looking at a person in the same ground plane. This argument doesnt hold for the front perspective, but the end result of such a perspective would be similar to looking in a mirror, and relating movement of our own body through a mirror is a challenge most of us have experienced at some point.

Visualization Idioms

We find the need to split the visualization prototype in two main parts: an overview and a detailed view. The separate parts should serve different purposes and follow a proven details-on-demand style where the overview is used to identify data subsets of interest and enable a temporal navigation once the user delve into details.

For the overview we make use of two streamgraphs [20] to represent the overall angle differences between the compared takes. So the data encoded in each streamgraph is categorically sorted (by joint) one-dimensional numerical values through time. The decision to use streamgraphs is based on the relative simplicity of the data along with the purpose of the overview visualization that is to provide an at-a-glance estimation of the distribution of the dataset and a way to identify interesting parts to look into. The few categories in the data also supports the use of streamgraphs. Because the ability to identify and relate to the categories present, which in this case are the respective joints, is not a main concern since they all add up towards the total difference between takes we decide to use a gradient coloring to emphasize the whole. We argue that the result is effective for identifying the interesting parts to study more closely because the thickness of the collective streams is a salient graphical feature as the individual streams become grouped together through the similarity in color.

When analyzing the data further, a richer picture should be painted through the use of small multiples. This idiom is chosen because of the nature of the data's internal relationships. Angles, angular speed and angular acceleration of each joint is temporal data that is closely related within each joint but not so much across joints. Because of this we do not want to use the same graph area for the different joints. Furthermore, because we make use of two perspectives, as previously elaborated on, the two angles defining each joint though similar in nature and of course related is incomprehensible when combined. The notion of angles in separate perspective planes is complicated and therefore we decide that the data has to be separated in the respective perspectives throughout the visualization. Lastly, the angle of a joint in one perspective, its angular speed and angular acceleration is inherently related but risks interfering with each other if merged into the same graph area. There is of course a problem with scale, which could be solved through multiple but aligned axes, but the two dimensional categorical distinction necessary to uniquely identify the type of data (angle, speed or acceleration) and which take it belongs to is a tougher issue.

Taking these things into account we decide on using the small multiples visualization idiom to be able to separate each perspective, each joint and each data type. This makes each graph a simple graph with two data series, one for each take, which can easily be identified throughout the visualization by using two unique colors. The trade-off of having so many separated graphs is the space available for each of them, which has consequences on the graphical features possible to add to the graphs and also what type of graphs are usable. We decide upon using line graphs for the small multiples because this is suitable for the temporally continuous movement data at hand and allows for deduction of values from each data series as well as an estimation of their difference at each time stamp. We minimize visual clutter by only showing labels on the y-axis of the graphs for joint angles, and exclude all labels but for the extreme points. The units for angular speed and acceleration are deemed non-relatable and therefore excluded for the sake of visual clarity. We argue that the ability to see the characteristics and relationship between the takes is

enough to make the graphs useful. The angles are more relatable and therefore the scale is labeled, but because of the size of the graphs we are forced to implement this in a minimal way, ending up with only the extreme points of the range.

The alignment and order of the multiples are related to the real-world semantically by aligning the joints by spatial relation in the body part (i.e. shoulder-elbow-wrist) and the data type by their mathematical relation (i.e. angle-speed-acceleration). To connect the temporal dimension across the small multiples we decide to display a line at the same position in all of them whenever a user hovers the mouse over any of the graphs. Finally a connection between the small multiples and the skeletal representations is deemed favorable as a way to communicate which joint each graph relates to, because the joints are identified even quicker in the skeleton than by a label stating the joints name.

Skeletal Representations

Skeletal representation of motion capture data is a proven technique which we decide to implement to make the visualization more comprehensible and relatable to the real-world. The visualization through streamgraphs and small multiples provides an analytical view of the data but without any skeletal representation they become distanced from the real-world. Using the skeletal representations to not only provide another look of the data but also to incorporate categorical descriptions and graph identification we argue that all parts of the visualization are enhanced in a relatable and space-efficient way. Because the visualization only treats one body part at a time, we decide to cut off the skeleton so that only the currently studied body part is visible together with the directly related joints that makes up the coordinate system. This allows us to increase the scale of the skeleton to provide a clear view and avoid any confusion regarding the motion or non-motion (depending on the way this would be implemented) of the rest of the skeleton. The trade-off is that the partial skeleton isn't as easily identified and parsed as a whole skeleton would be.

Use of Color

The main function of color in the visualization is to identify the two takes being compared. The decision to use color for this is based upon the desire to be restrictive with the limited visualization space and the importance of a user's ability to uniquely identify the takes through multiple graphs. The colors are selected after taking some potential different users and use cases into account. Because of the prevalence of color vision deficiency a blue and yellow hue, as can be seen in figure 2, were chosen to be uniquely distinguishable also for users with common color deficiencies such as protanopia and deuteranopia. Furthermore, the luminance of the colors is adjusted so that should a user print the visualization in grey scale the identification of takes by color should still be feasible.

To make the colors salient and the visualization as clear as possible we avoid additional, unnecessary, coloring in the visualization and its interface. When coloring the streamgraph



Figure 2. Colors to identify takes.

we use a coherent gradient to minimize the number of different colors used. The main concern when choosing the coloring scheme of the streamgraph was to avoid unintentional ties with the colors identifying the takes. Further explanation behind this choice is found in the part concerning visualization idioms.

Interactivity

As covered earlier, much of the interactivity in the visualization is to connect graphs to each other or to explain what part of the data each graph represent. Even though the user select a time period to study when initializing the visualization (by selecting start time and duration of the takes) we found that this functionality was not enough, which made us decide to implement a filtering mechanism inside the visualization. Naturally this is implemented in the overview visualization, the streamgraphs, because of their purpose of identifying sequences of interest. By adding a brush that filters out data and updates the detailed small multiples there is a clear temporal connection between the overview and the detailed view. Our argument is that this results in a powerful filtering tool that enables a closer look at the data by zooming the graphs in the detailed view.

IMPLEMENTATION

MoComp is developed as a web-application in JavaScript with libraries jQuery [18] and D3.js [19]. By designing it as an extension of MoVa we are able to take advantage of the file loading and skeleton drawing methods already implemented in MoVa. By using D3.js to create visualizations with SVG elements the application is cross-platform compatible and graphics are scalable without loss of quality. The source code of MoComp is available on GitHub at the following link: <https://github.com/mysunnytime/MoComp>. The prototype is accessible at: <http://www.sfu.ca/~yayingz/mocomp>.

Inside the toolbox of MoVa a new menu for comparison of movement takes (motion capture sequences) is added. In this menu, "Movement comparison", the user can choose two takes to compare. The user also selects starting time stamp and duration for the part of the takes to evaluate; for now this is done by text input. Finally a body part of interest is selected, the choice is between left arm, right arm, left leg and right leg. When all selections are made the visualization is initialized in an overlaying window by the compare button. Behind the scenes calculations are made to transform the set of mocap data to find angles of each joint in the body part, speed of angle change and acceleration of angle change.

Feature Extraction

As the visualization covers a body part at a time the dataset is reduced by filtering out the joints not relevant for the current focus. The feature of interest, the angles of joints, are then extracted from the reduced spatial positional data.

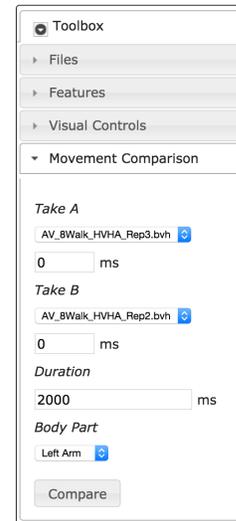


Figure 3. Initialization through the MoVa toolbox.

The first part of this process is to establish a body-dependent coordinate system and associated viewing perspectives. This is accomplished by identifying and translating three key joints to make up the basis of the coordinate system in each frame of the motion sequence. For the upper body the axes of the coordinate system are made out of the center-shoulder to spine vector, center-shoulder to right or left shoulder vector and a vector extending out of the body perpendicular to the previous two. Lower body axes are based upon center-hip and right or left hip instead of the corresponding shoulder joints.

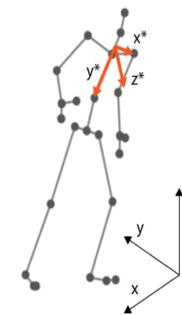


Figure 4. Bodydependent coordinate system.

The joints of the studied body part are then translated into the established coordinate system and projected to the two viewing perspective planes to allow for the extraction of angles in two 2D planes. Angles of each joint in the body part are calculated relative to the spine and later separated by removing the part caused by accumulation of rotation through the body part. Once the dataset is refined additional features of the movement, such as the speed and acceleration of joints and limbs, are derived simply by determining the rate of change in the angles between each frame of the data.

VISUALIZATION DESCRIPTION

Below follows a description of the prototype resulting from the research outlined in this paper.

MoComp: Movement Comparison

Bodypart: Left Arm
A: "movs/AV_8Walk_HVHA_Rep3.bvh", from 0 ms to 2000 ms
B: "movs/AV_8Walk_HVHA_Rep2.bvh", from 0 ms to 2000 ms

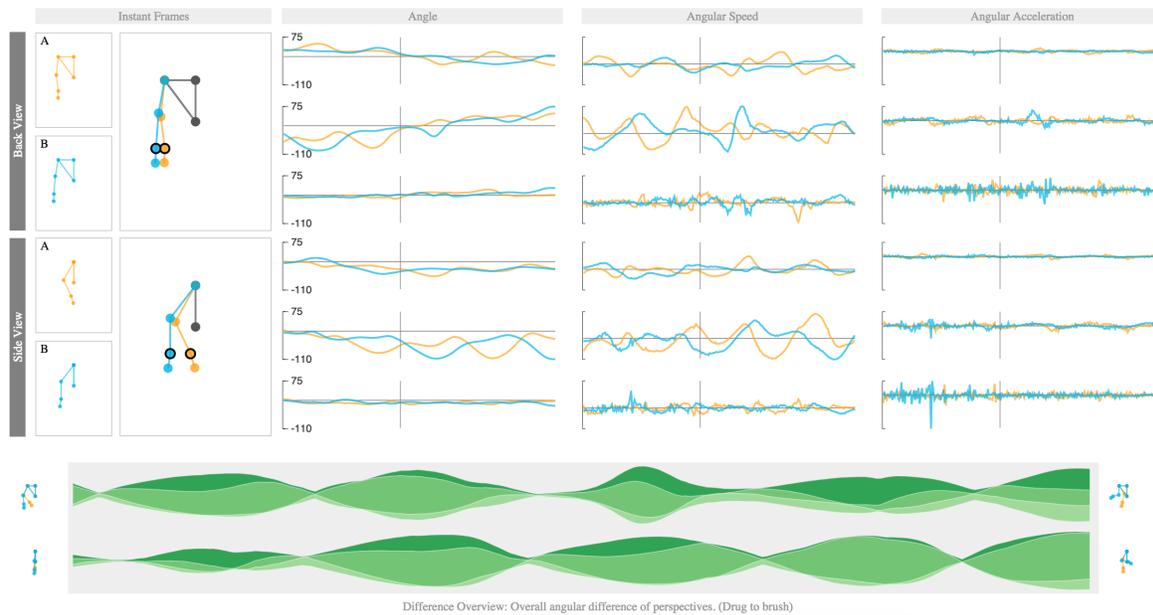


Figure 5. MoComp

Overview Visualization

To provide an overview, streamgraphs are constructed to visualize the overall difference in angles between the joints of the two takes. There is one streamgraph for each perspective of the movement, one from the back and one from the side of the skeleton. Each joint angle difference will be represented by one sub-stream in the graph. The joints are identified by position in stream and color in the gradient whereas the width of each stream is the angle difference between takes at each time stamp. At each end of the graphs are skeletal representations of the positional data at the start and end frames respectively.

The user can make interactive selections by clicking and dragging on parts of the graph. This will filter the dataset presented in the detailed visualization. The overview visualization is placed at the bottom of the window to provide context and allow for re-filtering the data throughout the interaction.

Detailed Visualization

Above the overview visualization the detailed time-dependent data view is presented, affording a more elaborate view of the differences in the selected time period. The data represented in this area is filtered by the selection in the overview visualization. The main visualization idiom used for details is small multiples. Just as the overview visualization this is also split for two perspectives. The small multiples consist of a set of line graphs for each joint. The set includes angle, angular speed and angular acceleration. This results in two 3x3 (3 joints x 3 dimensions for 2 perspectives) matrices of graphs.

In each graph the time-dependent data of each take is plotted in the same graph area. This allows for comparison between the takes. Consistently through the visualization the takes are identified by two separate colors. Mouse-over in any of the

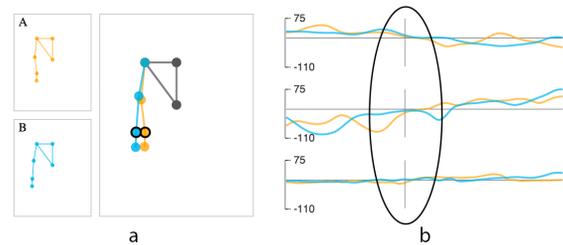


Figure 6. Skeletal representation and Detailed Visualization. (a) Skeletal representations in the focus frame view. (b) An example of highlighting on mouse hovering.

small multiples will display a line in all the others to emphasize their mutual temporal dimension and enhance comprehension.

The same interaction will also display the skeletal representation for the frame at the hovered time stamp in the frames at the left part of the window. In the skeletal representation the joint relating to the graph that is hovered over is highlighted to serve as a legend for the graph.

Skeletal Representation

In the left part of the window is the focus frame view, which concludes of six images presenting the skeletal position of the body part for any given time instance. Six images are needed to display the focus frame in each take separately and superimposed in both perspectives used. These images are shown at the left of the window, next to the detailed visualization. By hovering the mouse cursor over any small multiple the user will be shown the skeletal representation of the body part at that time stamp.

EVALUATION

At the end of this research we organized a semi-structured open-ended usage study. We invited two participants, both of which have research experience in movement analysis. One of the participants has an engineering background, while the other participant has an art background. The interview sessions happened in a quiet room and lasted for 20-30 minutes. The participants were asked to use the prototype and give feedback. Before they started the interviewer presented the purpose of this visualization tool and gave them necessary instructions to set off. While they were using the prototype the participants freely expressed their comments as the interviewers were sitting beside them observing their actions and communicating with the participants.

The focus of the usage study was: 1) how much does the user consider MoComp a useful movement comparison tool, 2) how much does the user consider MoComp as user friendly, easy to learn, and easy to control and 3) what other functionality or quality does the user expect from the comparison tool.

Two participants followed the same sequence of investigations: firstly they explored the prototype freely by their own and then they were guided by the interviewer to explore all the functionality in the prototype.

Both of the participants held very positive attitudes towards the prototype at first sight, as they started to explore it right after they had initialized the visualization. There was no need to provide much explanation to set them off investigating the prototype by themselves. They were curious and kept asking questions. After a brief explanation of the dimensions and on-going exploration, they reported the visualization as reasonable and sense-making.

However, there are some imperfections. The clarity might need improvement. Before being provided with an explanation, one participant was lost in the meaning of colors in the overview. Both of the participants suggested the skeletal representations to be a whole body skeleton with the focused body part highlighted rather than only displaying the bones and joints in the focused body part.

Moreover, some learning is needed to make use of this prototype as it incorporates several categories and dimensions of data-takes (Take A and Take B), perspectives (back view and side view), key joints (three key joints in a body part), and features (angle, angular speed and angular acceleration). The complexity leads to a difficulty of understanding, so a more intuitive system or better instruction is needed to reduce the learning cost of the user. The current interactivity, though deemed satisfactory in its functionality by the participants, was not immediately discovered in entirety which further increase the learning cost. Only the temporal highlighting on mouse hovering and subsequent updates of pose in the skeletal representation was discovered straight away, while the brushing in the overview remained undetected at first.

As the visualization was decoded the desire to adjust the temporal synchronization between the takes was expressed. This indicates that the users understood the visualization and the propagation of the data, but exposes an issue in the appli-

cation in its current state where temporal re-adjustment only can be done outside the visualization window as part of the initialization. This arrangement was also criticized for not providing enough information to the user; as the participants in the test approached the prototype with no knowledge of the movement takes at hand they expressed a wish to preview the takes and have some support in the selection of starting times and duration.

Lastly, participants wanted more options for the visualization. Participant one, the engineer, wished to compare other Laban features in the small multiples. He also wanted to extend the overview visualization with angular speed and angular acceleration. The other participant, the artist, expected more interactivity and possibilities to the prototype. She expected more components to respond to clicks and drags, without stating clear functionality expected from such actions. We notice that the expectation is influenced by the users expertise. The participant with engineering background has more functional expectations while the artist has more poetic expectations. This inspires us to be more user-centered in further work.

ANALYSIS

A key decision in the project was to make use of joint angles as the feature of choice for the comparative visualization, a decision we motivate earlier in the paper. When evaluating this at the end of the project no doubts arise as to if this was correct. In its final form the visualization provides a view of the data which is relatable to the real-world and ones own body, there was no doubts cast on this through the usage study. Of course, should the need arise the visualization and the platform developed through the project can be modified to encode any feature of movement the user might want to study. The most elaborate specialization on angular data are the body-specific coordinate systems and associated viewing perspectives, but even this isnt necessarily limited to angle data in its usefulness.

A consequence of the projects focus on the visualization of the prototype was some usability issues that became evident in the usage study. The initialization of the visualization in its current basic implementation ends up lacking functionality to preview takes and make use of more intuitive ways to determine the starting time stamp and duration of the takes. Currently the usage becomes slightly inaccessible without a clear cut objective and good knowledge of the motion capture takes at hand. This part of the prototype might have been somewhat neglected through the project as it was deemed less important than the visualization itself.

Moving on to the usability of the interactive visualization we found through the study that improvements to the affordance of the overview visualization should be looked into to make sure users find the functionality of its interactive brush. The highlighting on mouse over to communicate the temporal connection between the small multiples performed satisfactory but the highlighting of joints might not be salient enough in its current implementation.

As mentioned in the background, there is no consensus on the data format or structuring of motion capture data. Because of

the scope of this project issues arising from this had to be ignored and that unfortunately makes the prototype limited in what data it can parse. Through the design of the prototype we made efforts to simplify the adaptation needed to parse files with different hierarchical structure in the skeleton, so that an eventual extension to make the prototype more generally applicable can be added later on.

CONCLUSION AND FURTHER WORK

To tie in with the aim of the project; we have enabled a meaningful and accessible way to extract and comprehend differences in movement by developing an interactive visualization tool. The tool consists of an overview streamgraph visualization, a detailed small multiples visualization and skeletal representations of poses. The scope of the detailed visualization is controlled by an interactive filtering brush enabled in the overview visualization and the skeletal representations are updated in accordance with the highlighting of a time stamp done by hovering the mouse over any graph in the detailed visualization.

By using established visualization idioms after reducing and abstracting a large dataset, the tool is comprehensible and its interactivity is mostly intuitive. The features extracted and visualized are deemed useful but for further extensions of the prototype the addition of more features available for analysis is advised. Moreover, auto-analysis can be considered to facilitate the goal of movement comparison. Also, to make the prototype more accessible and useful, an enhanced initialization process (e.g. visualizing the movement takes to facilitate the synchronization) is recommended and perhaps possible through a closer integration with the previously established MoVa framework.

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