User Clustering Visualization and Its Impact on Motion-Based Interaction Design

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Abstract. Movement-based interaction design relies on sensor data analysis and higher-level feature extraction to represent human movement. However, challenges to effectively using movement data include building computational tools that allow exploring feature extraction technology as design material, and the need for visual representations that help designers better understand the contents of movement. This paper presents an approach for visualizing user clustering descriptors to enhance the practitioners' ability to use human motion in interaction design. Following a user-centered strategy, we first identified perceptions of, and barriers to, using motion-based features in a group of interaction designers. Then, a multiple-view multiple-people tracking system was implemented as a detection strategy that leverages current models for 3d pose estimation. Finally, we developed a computational prototype that performs instantaneous and short-term clustering of users in space and presents simple descriptors of the algorithm's output visually. Our approach was validated through a qualitative study with interaction designers. Semi-structured interviews were used to evaluate design strategies with and without the assistance of the computational prototype and to investigate the impact of user clustering visualization on the design of interactive experiences. From practitioners' opinions, we conclude that feature visualization allowed designers to identify detection capabilities that enriched the ideation process and relate multiple dimensions of group behavior that lead to novel interaction ideas.

Keywords: Interaction design · Machine learning · Feature visualization · Motion-based feature · User clustering

1 Introduction

Interaction design plays a crucial role in creating engaging and effective movement-based interactions. One of the key challenges in this field is finding systematic and predictable relationships between human movement and technology, which requires human movement analysis and feature interpretation. In recent

M. Kurosu and A. Hashizume (Eds.): HCII 2023, LNCS 14011, pp. 47–63, 2023.
https://doi.org/10.1007/978-3-031-35596-7_4

years, there has been a growing interest among the human-computer interaction community in exploring the possibilities of motion-based interaction design. This has led to the development of various computational frameworks for analyzing human movement, such as those proposed by [1,2,7,13]. These frameworks focus on the extraction of relevant features from human motion data, such as spatial, temporal, and qualitative characteristics, to better understand and represent the contents of human movement. However, despite the progress in this field and as concluded from the previous works, there is still a lack of understanding about how these movement characteristics are perceived by interaction designers and experienced by end users.

In our previous work [15], we gathered a group of interaction designers in a focus group study and identified perspectives and attitudes toward using motion-based features. The study explored how practitioners relate motion-based feature extraction technology and sensor-based interaction design methodologies, highlighting their perceptions of the conditions descriptors must meet to become a constructive exploration tool during concept ideation. In essence, we found that interaction designers demand features that provide valuable information for non-technical practitioners and help identify a path to design.

Beyond the type of detection system, movement features can be derived by using algorithmic methods [1,9,13,18] or by using machine learning techniques [7,19,20,23,29]. Unsupervised learning is used for detecting features of motion instead of explicitly defining rules or algorithms, offering the ability to characterize group behavior without reliance on a priori knowledge. Due to the manifested interest of interaction designers to use easy-to-understand motion-based multiple-people features [15], we decided to provide the ability to perform clustering to positional data over configurable time windows. Additionally, we followed their recommendations regarding feature interpretability and created meaningful visualizations with the extracted data. We foresee that user clustering visualization could be helpful to interaction designers when designing movement-based interactions because it allows them to identify common patterns and behaviors across different users, which can then inform the design of the interaction.

We implemented a multiple-view multiple-people tracking system and developed a computational prototype that visually describes the users' clustering to improve the practitioners' capability to use human motion in interaction design. The aim is to understand the impact of user clustering visualization on the design of interactive experiences and how the visualization of multiple user clustering descriptors encourages its use in the design of spatial-interactive experiences. We conducted an interview-based study and observed that movement information visualization provided further insights into the characteristics of movement and helped participants understand the interaction opportunities that come with it. Interaction designers harnessed such visualizations to identify detection capabilities and enrich the ideation process.

2 Background

In this section, we briefly present the related work on which we build our prototype. First, we examine algorithms and computational models to interpret human activity through feature extraction. Then, we discuss different techniques used to visualize movement and its characteristics.

2.1 Movement Feature Extraction

Significant prior work has been done in expressive gesture recognition [28], and performative art studies [1] to extract information from human movement. The *EyesWeb* processing library [8,10] proposes a set of expressive cues in a layered approach to model expressive gestures from low-level physical measures up to overall motion features. Following research [1,7,18,21] advanced in the study of human movement by using similar approaches for the analysis of expressive gestures in music and dance performances. More recent work has evolved the analysis strategy to a user-centered approach based on Interactive Machine Learning (IML) and Design by Doing [22]. Presented as a promising resource to design intricate and performative movement interactions, such as embodied movement [29], IML makes it possible to design by providing examples of correct behaviors framed in terms of supervised learning. Gillies [22] points to IML as a successful method for designing movement interaction with applications in a wide range of domains: from movement-based musical interface design [19,20] to rapid prototyping of movement in a participatory design context [11].

The *movement and computing* community has shown interest in developing computational frameworks for the analysis of human movement data in recent years. *Mova* [2] is a movement analytics framework for motion capture data integrated with a library of feature extraction methods. The framework allows examining several of the features proposed in the literature in terms of their operative or expressive qualities. *OpenMoves* [3] is a system for interpreting person-tracking data that emphasizes movement pattern recognition. The system was presented as a complement to *OpenPTrack* [27] and provides real-time centroid analysis, low-level short-time features, and higher-level abstractions based on unsupervised and supervised machine learning techniques. *Modosc* [13] is a library in the form of Max abstractions that extract movement descriptors from a marker-based motion capture system in real-time. The initial release of the library presented point descriptors like velocity, acceleration, jerk, and fluidity index along with descriptors to process groups of points such as center of mass, quantity of motion, contraction index, and bounding box. Finally, *InteractML* [23] is a node-based tool for designing movement interactions in Unity, based on the IML paradigm and tailored to non-experts with little programming experience. Nevertheless, among movement features to be used as inputs to the model, the user can only choose between position, rotation, velocity, and distance to another input.

2.2 Movement and Feature Visualization

A growing body of literature has investigated different ways of visualizing motion capture data [2,4,6,25]. Frequently applied strategies derive representations from raw data usually considering the extraction of features focused on exposing and extracting as much of the semantics as possible [6]. The analytics platform by Alemi et al. [2] uses parallel visual processing capabilities of human perception to visualize multiple features at the same time and in different forms which can be used to better understand the relationships between a particular type of movement and their corresponding measurable features. Extending Bernard et al.'s work [6] to the dance and performing arts domain, Arpatzoglou et al. [4] presented a prototype of their framework *DanceMoves* addressing these challenges. The framework's functionality offers the interactive visual analysis of dance moves, as well as comparison, quality assessment, and visual search of dance poses. The proposed similarity measures were evaluated using agglomerative clustering over a public domain dataset and the visualization features through domain experts' feedback. However, they neglect to discuss the methodology for the qualitative study that supports their conclusions. From a different perspective, *MoViz* [25] is presented as a visualization tool that enables comparative evaluation of algorithms for clustering motion capture datasets. Regarding the design of behaviors and user interface, *MoViz's* authors tried to include several information visualization design principles to make the tool intuitive, informative, and accurate in data representation. Using *LuminAI* [26] -an interactive art installation that uses machine learning to improvise movement with human dancers- as a use case, Liu et al. [25] employed *MoViz* to evaluate different gesture clustering pipelines used by the installation's AI system. As a result of this evaluation, the authors argue that the tool allowed them to identify which pipelines worked well for certain clustering datasets, which speaks to the tool's potential to better understand 'black-box' algorithms.

3 Prototype Implementation

To study the impact of user clustering visualization on motion-based interaction design, we developed a prototype to analyze human motion for interaction design purposes. Although the implementation was comprehensive by allowing a group of people to move freely with intentions of interaction within a large space, the specific contribution of this article assumes the use of the prototype as a research instrument, so the description of the system is complete yet brief.

3.1 Pose Estimation and Tracking in 3D Space

The 3d pose estimation and tracking component considers a multi-camera approach to account for large volume spaces and resolve occlusions and limited field-of-view problems. The procedure for this component consists of a sequence of steps. First, a calibration step based on using a *ChArUco* board pattern to capture properly synchronized images, and then obtain camera poses by bundle adjustment optimization. Second, a people detection and pose estimation step. To this end, we adopted the body-only *AlphaPose* estimator [17] which follows a top-down strategy. *Alphapose* is a two-step framework that first detects human bounding boxes and then independently estimates the pose within each box. In the current implementation, an off-the-shelf *YOLOV3* pre-trained detector [30] and an efficient high-accuracy pose estimator [17] are adopted. Third, a multi-view correspondence and 3d pose reconstruction step. To match the estimated 2d poses across views, we adopted the approach of Dong et al. [14] in which appearance similarity and geometric compatibility cues are combined to calculate the affinity score between bounding boxes. The bounding boxes with no matches in other views are regarded as false detections and discarded. The multi-way matching algorithm groups 2d poses of the same person in different views from which 3d poses can be reconstructed [5]. And fourth, a tracking-by-detection and filtering step to finally obtain smoothed human poses of all the people in the scene. To improve the identification ability, we compute the appearance feature similarity between non-redundant candidates and existing tracks to address the spatial distance limitation. Temporal averaging is used to fill in missing joints, while a Gaussian kernel with standard deviation σ is used to smooth each joint trajectory [31].

3.2 Feature Extraction System

The feature extraction system is based on identifying the joints in the human body and tracking all users in space. Moreover, the user's trajectory is characterized by considering a fixed number of the most recent position points updated into a circular buffer of three-dimensional data at every time step. To prevent the user from diverting his attention to technical details about algorithm tunning, we decided to reduce the prototype user intervention to its minimum. Therefore, neither algorithm parameterization nor numerical feedback is an option for the user. Below we present the features that were implemented for the present study.

Instantaneous Clustering. The instantaneous clustering feature takes the current time step's set of user centroid positions and finds clusters using the mean shift algorithm [12]. The mean shift algorithm is widely used in data analysis because it's non-parametric and doesn't require any predefined number of clusters. As Amin & Burke [3] pointed out, the mean shift algorithm fits well with the frequently changing nature of social interaction scenes and live performances.

Hotspots. The hotspots feature provides the capability to identify frequently visited areas or routes in the space. Based on the work of Amin & Burke [3], hotspots are addressed as a long-term, macroscopic form of clustering. Nevertheless, we decided to perform clustering to positional data over a fixed time window using a different algorithm. We have chosen the DBSCAN algorithm as it performs density-based clustering robust to outliers. DBSCAN works on the assumption that clusters are dense regions in space separated by regions of lower density [16], providing better hotspot visualization results compared to other clustering algorithms.

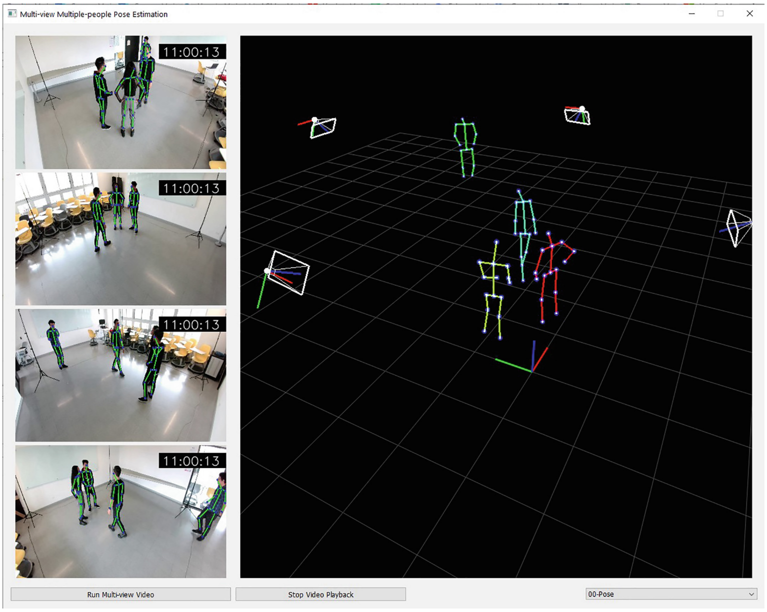

Fig. 1. Multi-view multiple-people tracking system.

3.3 Visualization Engine

The visualization engine provides visual representations of the human poses and the extracted features in a 3d view of the scene. The graphical user interface is divided into three sections (see Fig. 1): A selection section with controls for opening scenes and selecting the feature, a multi-view video playback section with the 2d pose detection results overlaid on each view, and a three-dimensional representation of the scene over which the feature visualization is rendered. The camera position in the 3d scene is controlled by the prototype user using six degrees of motion input using the keyboard keys and the mouse; allowing the user to observe the relationship between feature and space from different perspectives, navigate the 3d scene, and decide whether to focus on a smaller region or zoom outwards to get a broad overview. In addition, the prototype adheres to Tufte's conception of graphical integrity in which visual representations of data should neither overrepresent nor underrepresent its effects and phenomena [32]. Following we present the visualization strategies corresponding to each feature.

Instantaneous Clustering Visualization. To produce a meaningful feature visualization, we decided to maintain the color representation assigned to each user by the tracking module and not to change it depending on the cluster to which they belong each time step. Preliminary tests evidenced that coloring each user's pose according to the cluster produced confusing results that overrepresented the phenomenon with continuous color flips. Instead, we observed that using a fixed neutral color and a circular shape for displaying all clusters was more organic and intuitive. However, to offer a complete visual experience of the clustering attributes, we decided to represent the distance of users to the cluster's centroid to which they belong with lines on the ground plane, and the number of users in each cluster as the radius of the circle representing the cluster. As a final result, we present an instantaneous clustering visualization that prioritizes cluster position and size over cluster shape and eliminates information in the height axis (Fig. 2).

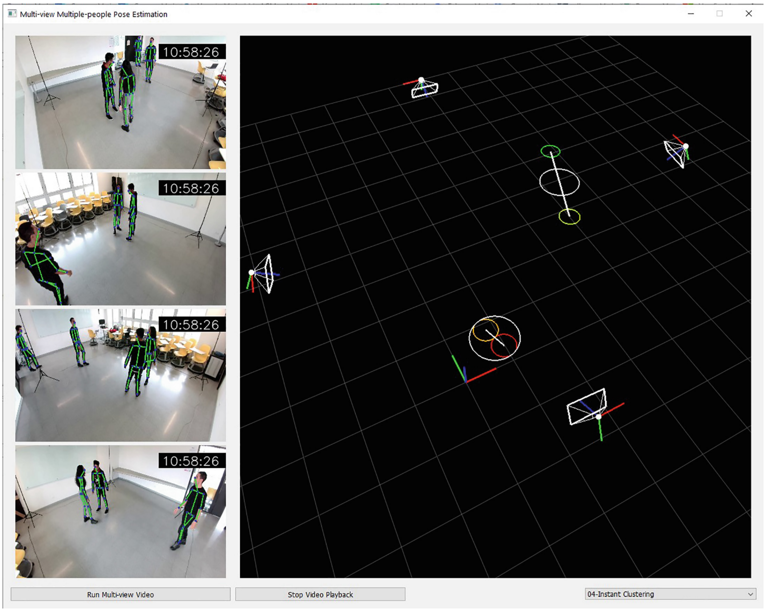

Fig. 2. Visualization of clustering over instantaneous positional data.

Hotspots Visualization. Regarding long-term clustering visualization, the prototype shows simple descriptors of the algorithm's output such as position, spread, and boundaries of clusters in a heatmap representation to enrich the user's perception of group behavior. The prototype maintains a 3d view of the scene to represent the user's trajectories and displays the hotspot representation on an emergent GUI widget (see Fig. 3). We noticed during development that the hotspot information by itself was not perceived as reliable if the trajectory information was unavailable. We believe that, in this case, as the length of the trajectories is the result of the time window considered by the clustering algorithm, its visualization allows a quick interpretation of the heatmap representation and validates the graphic outcome.

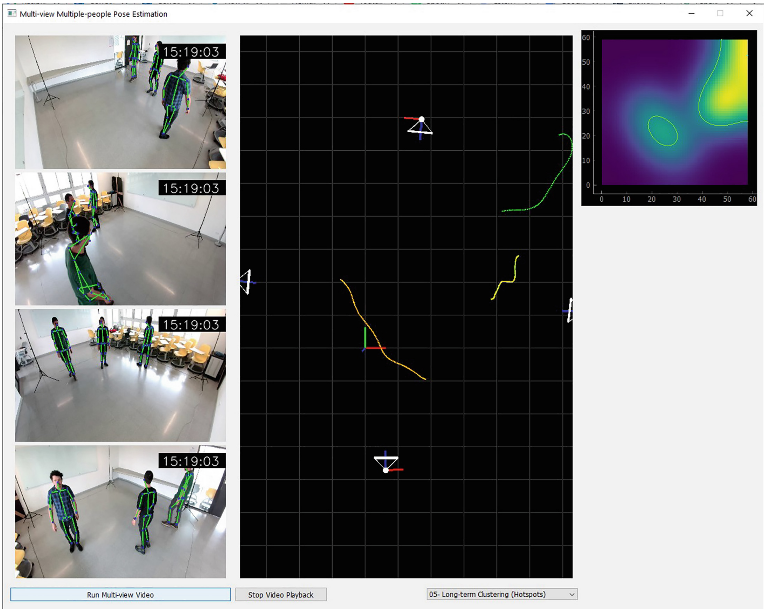

Fig. 3. Hotspot visualization

4 Proposal Assessment

A qualitative research method was used to follow a user-centered approach and to develop an understanding of interaction designers' needs and perceptions. We chose a semi-structured interview-based methodology to ensure we cover the breadth of experiences practitioners have when designing interactive experiences and observe the impact of user clustering features and their visualization in design practice.

4.1 Participants

Six interaction designers took part in the qualitative study. Three of these had participated in our previous study [15] and the other three participants were recruited specifically for this study. Nevertheless, the recruitment protocol was the same as for the previous study [15] ensuring that new participants had prior proficiency in creating full-body interactive experiences based on movement or gestures. This mix of practitioners allowed us to consider new interaction designers' perspectives and give continuity to previous participants' ideas in the prototype evaluation process. There were participants between the ages of 23 and 45 (M = 30.3, SD = 9.6), with professional experience varying from 3 to 15 years (M = 7, SD = 4.6).

4.2 Interview Method

Prior to the interview, three multi-view scenes with actors were recorded using a calibrated multi-camera system. Each scene recreated a particular situation where the grouping of people was considered suitable for the design of interactions in space. The interviews were conducted by the corresponding author using a web conferencing tool with activated webcams on both sides. The interviewer presented the research aims and briefly explained the contributions of our previous study. Two study conditions corresponding to the extracted features explained in Sect. 3.2 were considered. For each condition, we first presented a scene and discussed design strategies in the absence of any visual feedback other than the video itself. Then, we told participants that they would be presented with a user clustering visualization prototype. Finally, we asked them to interpret the user movement from the corresponding extracted feature and to express what other interactions they could think of with the information available. The discussion was repeated for the other two scenes, following up on topics of interest that arose naturally. After reviewing both conditions, participants were asked about aspects that influenced their overall experience, their thoughts on the hardship of assessing user grouping without proper visualization, and the limitations faced.

4.3 Analysis

The interview video recordings were initially reviewed as a method of immersion and preparation stage before the analysis. We used timestamps to identify interesting quotes and relevant sections, and reviewed insights retrospectively within the research team. To analyze the interview data, we first transcribed the audio recordings, then extracted discrete statements, and finally labeled them by condition. Moreover, we clustered the statements using grounded theory methods and affinity analysis [24] and then, performed open coding for major thematic groups. In a second clustering round, statements within these groups were then further analyzed and clustered into sub-categories. After multiple rounds of discussion and analysis with the research group, we observed a set of themes that emerged from the interview findings.

5 Results

The results section of this paper presents the findings from the qualitative research study. Through this method, we were able to identify several key themes and sub-categories that emerged from our analysis. As can be seen in Fig. 4, there were three main groupings that participants (P) discussed in different ways. First, participants considered user clustering visualization a valuable tool to better understand user behavior, which includes pattern identification and even anomalies in user behavior. Second, user clustering visualization helped practitioners refine their design practice and make more informed design decisions. Finally, practitioners acknowledged that this approach would be most ideally suitable during the analysis and evaluation stage or during the definition of motion-based detection strategies.

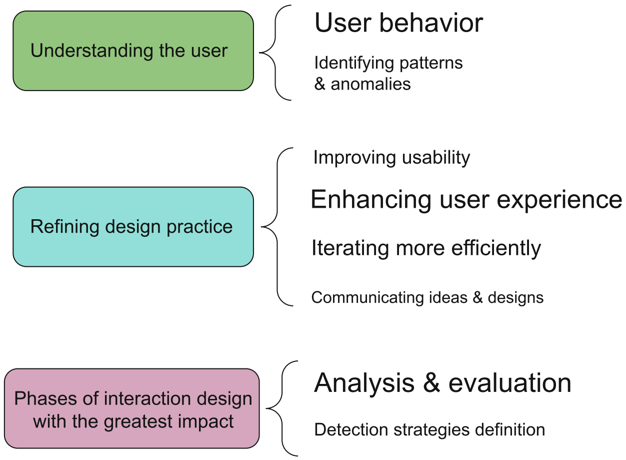

Fig. 4. Affinity analysis results with main themes and sub-categories. A bigger font size indicates that the topic was discussed by more participants.

5.1 Understanding User Behavior

One of the main themes that emerged from the data was the importance of understanding user behavior and identifying patterns and anomalies. Practitioners noted that user clustering visualization allowed them to better understand the diverse ways in which users interact with the system and identify areas where the design may be falling short.

Understanding User Behavior. Feature visualization allowed designers to understand how users move and interact with a product, providing insights into user behavior and preferences.

- "User clustering visualization helps me to see where users are having difficulty, and to identify patterns of behavior that I might not have noticed otherwise." (P4)
- "I think what matters most in that scene is where they stand and the interactions they are making in mid-air." (P2)
- "There is something interesting, and it is to understand that the feature is a specific information of the movement that opens the additional possibility of predicting the user's behavior." (P5)

Identifying Patterns and Anomalies. By visualizing movement descriptors, designers could identify patterns, such as common gestures or movements, as well as anomalies or unexpected behaviors.

– "The information provided by the prototype can be used to develop an active play installation using gross motor skills. You could analyze group patterns and make a game out of them." (P2)
– "It occurs to me that you can know two people from the same team, in what position they are one with respect to the other. And define whether they are fulfilling a condition, for example, you are 'offside' or you are not. You're ahead or you're not, those kinds of interactions. I think they are interesting." (P2)

5.2 Refining Design Practice

Another key theme that emerged from the data was the role of user clustering visualization in supporting some of the designer's work. Participants stated that user clustering visualization helped them in design practice by improving usability, enhancing user experience, iterating more efficiently, and communicating ideas and designs to other stakeholders. They noted that this approach allows them to make more informed design decisions, and to communicate their ideas more effectively to, for example, developers and engineers.

Improving Usability. With a better understanding of how users interact with a product, designers can make informed decisions about the design of movement-based interactions, resulting in improved usability.

– "Interesting! The group movement in this visualization looks natural and fluid. I would use it not only to implement an interactive experience but to measure its effectiveness." (P3)
– "User clustering visualization has been really helpful in identifying areas where the design is not working well, and in coming up with solutions to improve usability." (P5)

Enhancing User Experience. By incorporating user behavior insights into the design of movement-based interactions, designers could think of a more personalized and engaging user experience.

– "I would use the user's distance to all other clusters in a game to influence what the other groups of people produce even if to a lesser extent." (P4)
– "The interior design of commercial spaces has some rules, right? Then, depending on the user's trajectory, the intent of those rules can be reinforced with lighting, for example. Now I can detect where the user stops and based on this event, understand which are the objects, or at least the category of objects, that attract the most attention." (P6)
– "By observing a trajectory, I can be very sure of where the user has passed, and I can make redesign decisions with certainty based on an analysis over time." (P5)

Iterating More Efficiently. Feature visualization provided designers with a quick way to iterate on their design ideas, allowing them to adjust and test different options more efficiently.

– "It's just that the features make it much easier. For example, clustering and trajectories are very good for understanding how groups are formed. One now compares the features and the videos, and it is not easy to realize all the information in the movement that can be useful." (P3)
– "It helped me to see where users are having trouble and to iterate more quickly to improve the overall user experience." (P1)

Communicating Ideas and Designs. Additionally, practitioners expressed that feature visualization could be used as a tool for designers to communicate their ideas and designs to other stakeholders, such as developers, engineers, and other designers, allowing for a more collaborative design process.

– "The prototype is very useful for me to ground the idea and take it to other fields of ideation." (P1)

5.3 Impact on the Full Design-Production Cycle

Finally, practitioners commented on the stage/phase of the design-development cycle in which this approach would be most suitable. All of them were unanimous in their assessment of the prototype as an effective tool for the analysis and evaluation of group experiences; however, some other opinions also pointed toward using the prototype during the definition of motion-based detection strategies. They emphasized that clustering visualization is particularly useful in helping designers to define the specific movements or gestures that will be used to interact with the system and in validating the effectiveness of different detection strategies.

During the Analysis and Evaluation. User clustering visualization can be particularly useful in motion-based interaction design, as it can help designers understand how different groups of users interact with the system and identify potential issues or challenges. This process is typically used during the analysis and evaluation phase of the interaction design process.

– "In this scene, it was 'cool' to see a heat map with a lot of the information that I had previously with lower-level features. It's all there, and now I can analyze where they were moving! It is certainly easier for me to see it because of the type of visualization." (P3)
– "For me, it is useful not only to control the experience as such but also to measure its long-term success. This is one of the most difficult things in the design of interactive experiences since in most cases the only feedback we have is through satisfaction interviews." (P1)

During the Definition of Motion-Based Detection Strategies. To a lesser extent, the discussion of the participants focused on how user clustering visualization can be useful throughout the interaction design process, not just in the analysis and evaluation phase. One key phase where user clustering visualization was particularly valuable was in the definition and design of motion-based detection strategies.

– "When you're designing experiences, it's important that there are certain things that are kind of magical and abstract, right? But also, that they allow some understanding of how user interaction works in order to control the experience. Otherwise, people come in, and if they don't understand, they leave. So, it also seems to me that it is, in a certain way, a matter of easy understanding for the user." (P1)
– "In clustering, I see that there are several data available that are, in a certain way, parameterizable. Not only for the user, as an interaction parameter, but as a robust control event in the implementation stage." (P5)
– "I'm thinking about how long the user must take to make the gesture and how to detect it. It is these types of parameters that at the end of the day would define the rhythm of the experience." (P3)

6 Discussion

User clustering visualization is a technique used to group users based on their movement patterns and behaviors. This can be useful for interaction designers when designing movement-based interactions because it allows them to identify common patterns and behaviors across different users, which can then inform the design of the interaction. One specific benefit of user clustering visualization is that it allows designers to identify edge cases and outliers in user behavior. By understanding how these users interact with a product, designers can make informed decisions about how to handle these cases in their designs, resulting in a more inclusive and user-friendly interaction. Additionally, user clustering visualization can be used to personalize the user experience. By grouping users based on their behavior, designers can create tailored interactions for different user segments. This can lead to a more engaging and satisfying experience for users. Finally, user clustering visualization can also be used to improve the overall usability of a product. By identifying common patterns in user behavior, designers can optimize the interaction design to make it more intuitive and user-friendly for most users.

During the analysis and evaluation phase of the interaction design process, designers use various methods to gather data about users, such as interviews, surveys, and usability testing. This data is then analyzed to identify patterns and commonalities among users, which can inform the design of the final product. User clustering visualization can provide valuable insights for interaction design and can help designers create more effective and user-centered designs. For example, if a cluster of users is found to have difficulty with certain gestures or movements, the designer can take this into consideration and adjust the design to improve usability for that group. During the early stages of the design process, designers often need to define the specific movements or gestures that will be used to interact with the system. User clustering visualization can be used to identify common patterns and variations in user movement, which can inform the design of detection strategies that are robust and able to accommodate a wide range of user input. For example, imagine that you are designing a motion-based control system for a home automation system. Through user research and clustering visualization, you identify that users exhibit a wide range of hand gestures when controlling the system. Some users prefer to use simple, open-handed gestures, while others use more complex, closed-handed gestures. By understanding these variations in user movement, you can design a detection strategy that is able to accurately recognize both types of gestures. Additionally, clustering visualization can be used to validate the effectiveness of different detection strategies. By comparing the behavior of users in different clusters, designers can identify areas where the detection system may be struggling and adjust accordingly.

We argue that the visualization of user movement descriptors helps creators define better detection strategies that can lead to a more fluid interactive experience and reduced user frustration. When a motion-based detection system is able to accurately recognize a wide range of user input, it can respond to user actions more quickly and accurately. This can result in a more responsive and intuitive interface, which can make it easier for users to accomplish their tasks and reduce the likelihood of frustration. In addition, better detection strategies can also contribute to the creation of a natural user interface. When a motion-based detection system is able to recognize and respond to a wide range of user input, it can more closely mimic the way that people naturally interact with the environment. This can make the interface feel more natural and intuitive, which can reduce the cognitive load on the user and make it easier to use.

Practitioners should be aware that clustering is a complex process that requires a deep understanding of the domain, the user, and the technology. It should be approached with a critical perspective, considering the context, the goals, and the limitations of the project. Also, it's important to note that clustering visualization should be used in conjunction with other evaluation methods, such as usability testing, to provide a more comprehensive understanding of the system's performance. Moreover, the concept of a natural user interface goes beyond motion recognition. It encompasses various aspects such as the user interface, the interaction, the feedback, the aesthetics, the context, and the goals. Therefore, it's important to approach it with a holistic mindset, considering all these elements and testing the design with users.

7 Conclusion and Future Work

In summary, the feature visualization process was highly valued by the interaction designers participating in the study as it provided them with a valuable tool to structure and refine their design ideas. It helped them to understand the movement patterns of users, identify common behaviors and tailor their interactions accordingly. The visualization also allowed them to overcome the complexity of the extraction algorithms and explore the creative possibilities of using clustering and other features. The exposure to visual cues rather than numerical data was deemed crucial in their design practice as it helped them to understand user behavior in a more intuitive and graphical way. The practitioners reported that it was very difficult to abstract the meaning of the data without the prototype, and by observing a trajectory, they were able to make redesign decisions with certainty based on an analysis over time. Overall, feature visualization was seen as a powerful tool to enhance the design of movement-based interactions.

In future work, we plan to further investigate the impact of user clustering visualization on the design of interactive experiences. We will conduct user studies to evaluate the effectiveness of the system in different scenarios and domains. Additionally, we will explore the integration of other machine-learning techniques to improve the accuracy and robustness of the user clustering algorithm. Furthermore, as a new line of research, one can investigate the potential of using our approach in other fields such as crowd analysis, sports analysis, and surveillance.

References

1. Alaoui, S.F., Bevilacqua, F., Jacquemin, C.: Interactive visuals as metaphors for dance movement qualities. ACM Trans. Interact. Intell. Syst. **5**(3), 13:1–13:24 (2015)
2. Alemi, O., Pasquier, P., Shaw, C.: Mova: interactive movement analytics platform. In: Proceedings of the 2014 International Workshop on Movement and Computing - MOCO 2014, Paris, France, pp. 37–42. ACM Press (2014)
3. Amin, S., Burke, J.: OpenMoves: a system for interpreting person-tracking data. In: Proceedings of the 5th International Conference on Movement and Computing, p. 13. ACM (2018)
4. Arpatzoglou, V., Kardara, A., Diehl, A., Flueckiger, B., Helmer, S., Pajarola, R.: DanceMoves: a visual analytics tool for dance movement analysis. In: EuroVis 2021 - Short Papers, p. 5 (2021)
5. Belagiannis, V., Amin, S., Andriluka, M., Schiele, B., Navab, N., Ilic, S.: 3D pictorial structures revisited: multiple human pose estimation. IEEE Trans. Pattern Anal. Mach. Intell. **38**(10), 1929–1942 (2016)
6. Bernard, J., Vögele, A., Klein, R., Fellner, D.: Approaches and challenges in the visual-interactive comparison of human motion data. In: Proceedings of the 12th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications, Porto, Portugal, pp. 217–224. SCITEPRESS - Science and Technology Publications (2017)
7. Bevilacqua, F., Guédy, F., Schnell, N., Fléty, E., Leroy, N.: Wireless sensor interface and gesture-follower for music pedagogy. In: Proceedings of the 7th International Conference on New Interfaces for Musical Expression, pp. 124–129 (2007)

8. Camurri, A., Volpe, G., De Poli, G., Leman, M.: Communicating expressiveness and affect in multimodal interactive systems. IEEE MultiMedia **12**(1), 43–53 (2005)
9. Camurri, A., et al.: EyesWeb: toward gesture and affect recognition in interactive dance and music systems. Comput. Music J. **24**(1), 57–69 (2000)
10. Camurri, A., Mazzarino, B., Volpe, G.: Analysis of expressive gesture: the EyesWeb expressive gesture processing library. In: Camurri, A., Volpe, G. (eds.) GW 2003. LNCS (LNAI), vol. 2915, pp. 460–467. Springer, Heidelberg (2004). https://doi.org/10.1007/978-3-540-24598-8_42
11. Caramiaux, B., Altavilla, A., Pobiner, S.G., Tanaka, A.: Form follows sound: designing interactions from sonic memories. In: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul Republic of Korea, pp. 3943–3952. ACM (2015)
12. Comaniciu, D., Meer, P.: Mean shift: a robust approach toward feature space analysis. IEEE Trans. Pattern Anal. Mach. Intell. **24**(5), 603–619 (2002)
13. Dahl, L., Visi, F.: Modosc: a library of real-time movement descriptors for marker-based motion capture. In: Proceedings of the 5th International Conference on Movement and Computing, MOCO 2018, pp. 1–4. Association for Computing Machinery, New York (2018)
14. Dong, J., Jiang, W., Huang, Q., Bao, H., Zhou, X.: Fast and robust multi-person 3D pose estimation from multiple views. In: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, pp. 7784–7793. IEEE (2019)
15. Escamilla, A., Melenchón, J., Monzo, C., Morán, J.A.: Interaction designers' perceptions of using motion-based full-body features. Int. J. Hum. Comput. Stud. **155**, 102697 (2021)
16. Ester, M., Kriegel, H.P., Xu, X.: A density-based algorithm for discovering clusters in large spatial databases with noise. In: KDD, vol. 96, pp. 226–231 (1996)
17. Fang, H.S., et al.: AlphaPose: whole-body regional multi-person pose estimation and tracking in real-time. IEEE Trans. Pattern Anal. Mach. Intell. (2022)
18. Feldmeier, M., Paradiso, J.A.: An interactive music environment for large groups with giveaway wireless motion sensors. Comput. Music. J. **31**(1), 50–67 (2007)
19. Fiebrink, R., Cook, P.R., Trueman, D.: Human model evaluation in interactive supervised learning. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Vancouver, BC, Canada, pp. 147–156. ACM (2011)
20. Françoise, J., Candau, Y., Fdili Alaoui, S., Schiphorst, T.: Designing for kinesthetic awareness: revealing user experiences through second-person inquiry. In: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, Denver, Colorado, USA, pp. 5171–5183. ACM (2017)
21. Friberg, A.: A fuzzy analyzer of emotional expression in music performance and body motion. In: Proceedings of Music and Music Science, vol. 10, pp. 28–30 (2004)
22. Gillies, M.: Understanding the role of interactive machine learning in movement interaction design. ACM Trans. Comput.-Hum. Interact. **26**(1), 5:1–5:34 (2019)
23. Hilton, C., et al.: InteractML: making machine learning accessible for creative practitioners working with movement interaction in immersive media. In: Proceedings of the 27th ACM Symposium on Virtual Reality Software and Technology, Osaka, Japan, pp. 1–10. ACM (2021)
24. Lazar, J., Feng, J.H., Hochheiser, H.: Research Methods in Human-Computer Interaction. Morgan Kaufmann, Burlington (2017)
25. Liu, L., Long, D., Magerko, B.: MoViz: a visualization tool for comparing motion capture data clustering algorithms. In: Proceedings of the 7th International Con-

ference on Movement and Computing, Jersey City/Virtual, NJ, USA, pp. 1–8. ACM (2020)
26. Long, D., Liu, L., Gujrania, S., Naomi, C., Magerko, B.: Visualizing improvisation in LuminAI, an AI partner for co-creative dance. In: Proceedings of the 7th International Conference on Movement and Computing, Jersey City/Virtual, NJ, USA, pp. 1–2. ACM (2020)
27. Munaro, M., Basso, F., Menegatti, E.: OpenPTrack: open source multi-camera calibration and people tracking for RGB-D camera networks. Robot. Auton. Syst. **75**, 525–538 (2016)
28. Noroozi, F., Corneanu, C.A., Kamińska, D., Sapiński, T., Escalera, S., Anbarjafari, G.: Survey on emotional body gesture recognition. IEEE Trans. Affect. Comput. **12**(2), 505–523 (2021)
29. Plant, N., et al.: Movement interaction design for immersive media using interactive machine learning. In: Proceedings of the 7th International Conference on Movement and Computing, MOCO 2020, pp. 1–2. Association for Computing Machinery, New York (2020)
30. Redmon, J., Farhadi, A.: YOLOv3: An Incremental Improvement (2018)
31. Tanke, J., Gall, J.: Iterative greedy matching for 3D human pose tracking from multiple views. In: Fink, G.A., Frintrop, S., Jiang, X. (eds.) DAGM GCPR 2019. LNCS, vol. 11824, pp. 537–550. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-33676-9_38
32. Tufte, E.R.: The visual display of quantitative information. J. Healthc. Qual. (JHQ) **7**(3), 15 (1985)