Vision, Modeling, and Visualization (2022)
J. Bender, M. Botsch, and D. Keim (Eds.)

Visualizing the Movement of Space-Defining Rotatable Elements in Architecture

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Abstract

Space-defining rotatable architectural elements enable inhabitants to reshape the living space to their needs. In a field study, a prototype home was built that includes various multifunctional elements such as a rotatable wall, closet and lamps. Over the course of multiple months, multivariate time-series data was collected using sensors placed in the prototype home. To visualize frequent element constellations and to compare constellations across different user groups and periods of time, we developed a visualization system that embeds rotation distributions on the floor plan. Based on the visualization, we report on observations made by the researchers from the field of architecture and sociology.

CCS Concepts

• ***Human-centered computing*** $\rightarrow$ ***Visualization application domains;***

1. Introduction

In the European Union (EU-27), the number of single-adult households increased in the last decade by about 18% [Eur19], which was a 4.5× faster growth than couple households. This increase demands for small apartments able to accommodate a wide range of lifestyles [Kli13]. *Performative architecture* adapts the design of the environment to the challenges and needs of the inhabitants, opening new possibilities to use space [KM05, Nev17, FR16, Bac14]. A question in architectural practice that is still subject to debate is how and whether movable elements, such as rotatable walls or lamps, are actually used in domestic environments [Loc11]. To get closer to an answer, the collaborating architecture researchers conducted a field study, in which sensor data was recorded from test subjects living in a prototype home. We visually analyzed how inhabitants adapted the architecture themselves to their needs, in our case by the orientation of rotatable elements. The collection of such data through sensors provides a unique opportunity to explore spatial interactions of building components and behavioral patterns of inhabitants in performative architecture. Since the data is time-dependent and contains many variables, visualizations are an ideal approach to assess the data quality and to find patterns. Using our visual data analysis, the collaborating architecture researchers made interesting observations that can be further researched in a sociological context.

2. Background

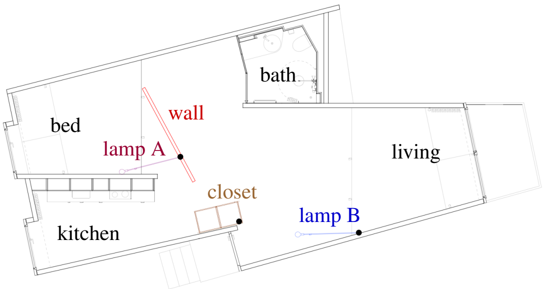
In the following, we describe the field study, the measured data, as well as give an overview of related work.

2.1. Mock-Up

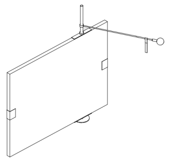
The sensor data was captured in a prototype apartment, later referred to as the *Mock-up*. Figure 1a gives an overview of the floor plan, showing kitchen, bathroom, bed and living area. A rotatable wall and a rotatable closet allow the inhabitants to close off or open areas and thus redirect light. The rotatable closet features two separate compartments. One can be accessed from the front and the other from the back, see Figure 1c. Further performative elements are two rotatable wall lamps to redirect the artificial light as well. We refer to the lamps as lamp A, which rotates around the same anchor point as the rotatable wall, and lamp B, which is mounted on the wall in the living area. Note that the wall and lamp A can be rotated independent from each other. All rotatable elements are shown in Figs. 1b–1c and photographs are presented in Figs. 1d–1e.

2.2. Data Collection

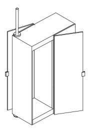
Test Subject Data To find diverse test subjects, in terms of origin, education, age, and interests, calls for applications were placed in various reports on the project in local and national newspapers, both printed and digital. Residents were chosen using an application form, letter of motivation, age and occupation. The selected test subjects lived as singles or pairs, representing single and two-person households, in the Mock-Up for one week each. Two-person households could consist of couples, roommates or other forms of living. For sake of simplicity, they are summarized in this work as *pairs*. For data protection reasons, all participants were anonymized and signed an agreement with information on the data collected. Data



(a) *Floor plan with rotatable elements*



(b) *Wall and lamp A*

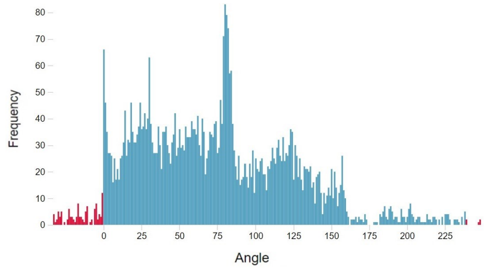


(c) *Closet*

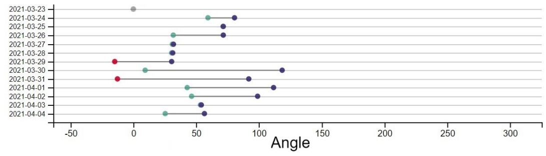
(d) *View from bed area.*

(e) *View from living area.*

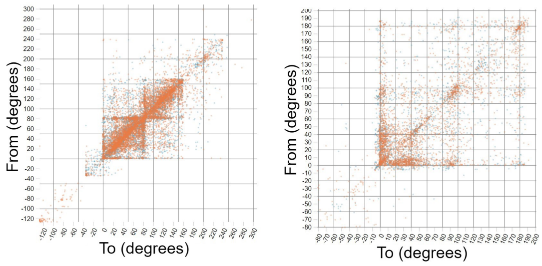
Figure 1: *A floor plan of the Mock-up shows the four rotatable elements all at zero degree angle as defined by the sensors and with different colors. Red for wall, brown for closet, purple for lamp A and blue for lamp B. Centers of rotation are shown as black circles.*



(a) *Angle histograms detect implausible outliers in red.*



(b) *Daily rotation range for lamp A using Cleveland plot shows minimal (green) and maximal (purple) angle recorded per day.*



(c) *Scatter plot matrix of* from–to *pairs for rotatable closet (left) and wall (right) show sensor uncertainty around common angles.*

Figure 2: *Analysis of sensor data quality.*

was collected over a period of 19 months. Each week, the previous test subjects moved out until Monday, 11am. The facility management cleaned the apartment each Monday from 12am to 4pm, and the new test subjects moved in on Monday afternoon around 5pm. For interactive filtering of the data, we consider the type of household (1-person or 2-person), the gender of the inhabitants (where *both* corresponds to a mixed 2-person household), the occupation category (student, full-time, part-time, unemployed) and the age brackets ($18-30$, $30-45$, $45-60$, $60-75$).

Sensor Data The Mock-up contains one rotation sensor on each rotatable element. The rotation sensors capture continuous information about rotations, recording the time the rotation started, the angle the element was moved *from*, the angle it was moved *to*, and the total duration of the movement. Fig. 2 gives an overview of the collected sensor data and shows our efforts in data quality assessment [VdBACEH05, LAW*18]. For example, a histogram of frequency of use per angle, as shown in Figure 2a for the rotatable wall, indicating how often an element was rotated to an angle outside of its physically valid value range. The red angles are not plausible and were clamped to the possible value range. However, the histogram does not include a time axis, Therefore a variant of the Cleveland dot plot was added, see Figure 2b. It visualizes all rotations by marking the *from* and *to* angle as well as the direction of the rotation. Based on the color of the dots one can tell whether an invalid value was recorded or whether the previous *to* value did not match the next *from* value (red). This allows identification of specific periods of times with miss-calibrations of sensors. Furthermore, on-site testing of the sensors revealed possible causes for mismatched values such as fast back-and-forth movements. Once this problem was detected at an early stage of the study, all rotatable elements were brought back to the zero degree configuration at the beginning of the week before the next test subjects moved in, which provides a reference for correction. Visualizing where a rotatable element was rotated from and where it was rotated to reveals usage patterns, such as preferred angles. Figure 2c displays the *to* and *from* angles, respectively, where each point corresponds to one rotation. To emphasise clusters of points, we displayed the points transparently. This way we can incorporate frequency information, as clusters stand out more than single points. Points on the diagonal of the plot represent small rotations. Points that cluster to a vertical or horizontal line show angles that were often moved *to* or *from*, respectively. In Figure 2c, we can see a strong preference for 0 degree, 90 degree and 180 degree rotations of the rotatable closet. The spread of angles around preferred orientations indicates measurement offsets and uncertainties, which we found to be at the order of about five degrees.

2.3. Related Work

Analysis of Human Behavior in Architecture This research project follows a Living Lab [RH17, Kro12] approach. It combines social, engineering and behavioral sciences with design research to understand the factors that influence user behavior in the content of architectural spaces. One interesting early study is PlaceLab [ILB*05, ILT*06], which is a live-in laboratory studying how to integrate ubiquitous computing technologies in the home. Ivanov et al. [IWSK07] monitored indoor spaces occupied by a large number of people over a longer period of time using sensors and video cameras to reconstruct the traces of a person. Rout and Willett [RW21] tracked human traces across a campus. In the context of human-building interaction (HBI), Lee et al. [LLZ*21] tracked social interactions from vision data in an office environment to study how the office layout constraints human interaction. In the visualization community, König et al. [KLK*21] visualized temperature measurements over time in a building, While the aforementioned works partially focus on tracking change and motion of humans in space, they considered this space to be fixed. Thus, they did not provide the pivotal performative aspect of our work.

Time Series Visualization The sensor measurements provide us numerous spatially-referenced time series. Multi-variate time series data is frequently studied in visualization research. Aigner et al. [AMST11], categorized time visualization methods based on the characteristics of the data. In our case, the whole data set is linear in time and ordered. In the following, we refer the reader to a selected set of approaches that facilitate different retrieval tasks from the data. One common goal is to identify similar events, which requires the definition of similarity measures. Li et al. [LCZ*19] discovered temporal relationship patterns across different event locations. Thereby, similarity is defined over time spans and multiple time series can be compared with each other. Bach et al. [BSH*16] folded time lines to bring similar points of the same time series closer together. Here, similarity was defined between all pairs of data points of one time series. In our work, we are interested in the usage of different elements, where the rotation angle of each can be seen as time series. Another goal is to enable the retrieval of patterns. Cappers and van Wijk [Cv18] investigated aggregation methods to define and retrieve events in multi-variate event sequences. Events are thereby defined as instantaneous data points. In their work, the data did not have a spatial reference. Izakian and Pedrycz [IP14] used clustering techniques to detect anomalies in spatiotemporal data by first defining anomaly measures. Vrotsou et al. [VJC09] employed graph similarity metrics to explore sequences of event-based data. Geolocalized data visualization was a frequent subject of research for spatial and temporal data exploration [AAG03]. Recently, Andrienko et al. [AAA*21] proposed query approaches to enable localization of time spans involving combinations of events, such as the co-occurence of movements. For a comprehensive introduction to time series data visualization, we refer to Aigner et al. [AMST11] and Brehmer et al. [BLB*17]. Next, we introduce the analysis requirements, which will inform the visualization approaches we take.

3. Requirements

The usage of rotatable space-defining elements is of high interest to understand how humans utilize and adjust living space given the opportunity to modify it. Due to the long time spans, the heterogeneity of the test subject data, the noise in the measurements, and the spatial context of the sensors, the effective data analysis is challenging, which calls for an interactive analysis by means of visualizations. The users of the visualization system are the collaborating architecture researchers, who use the system in a one-off analysis to explore and study the captured data. The following requirements and visualization goals have been derived from common visualization principles (detail on demand, linking and brushing), and the priorities and hypotheses to be tested have been iteratively refined in close collaboration with architecture researchers, as more of the data became visible. Sedlmair [SMM12] refers to this as the iterative design process in a design study. Further, contextual inqueries have been conducted on-site in the apartment, where the architecture researchers demonstrated the sensor setup, demonstrated vibrations that might impact the sensor accuracy, and explained the questionnaire procedure. One visualization researcher lived in the apartment for one week to experiment with the sensor accuracy.

R1: Temporal Analysis More than 36,000 sensor measurements were captured over a period of 19 months. In order to select a time range of interest a temporal overview of the time series data is needed that aggregates information and allows for the detection of missing data and patterns.

R2: Spatial Mapping of Elements All sensors have a spatial reference on the floor plan and produce time series information that varies due to differences among the test subjects. By embedding the information in a spatial context, general trends in the use of the rotatable elements should be identifiable. In particular, the spatial arrangement of multiple elements in conjunction is of interest.

R3: Interactive Filtering A key requirement for the spatial and temporal analysis is the joint visualization and filtering of events in space and time, and based on the test subject specific meta information in order to identify dependencies and patterns.

4. Visual Analysis of Space-Defining Elements

To meet the requirements listed above, we develop an interactive visual analysis tool that allows the users to fulfill abstract tasks. The tasks were derived according to the action-target model by Munzner [Mun14], which enables reasoning about appropriate visual encodings and interaction idioms, independent of the application domain at hand. Afterwards, we describe the design of visualizations for solving the task T1–T3 in more detail.

T1: Find Entry Point for Exploration (R1 and R2) The interactive exploration of the data follows an overview-first and detail-on-demand approach. Thus, by means of *summarization*, we give both a spatial overview of the sensor angle distributions in the context of the floor plan, and we perform a temporal aggregation that allows for both *locating* events of a specific user group and *browsing* for events around a given time. Both analysis tasks provide an entry point to the further visual exploration of spatial and temporal behavior.

T2: Extract Details for Individual User Groups and Time Ranges (R1 and R2) For a given time range and a given test subject group,

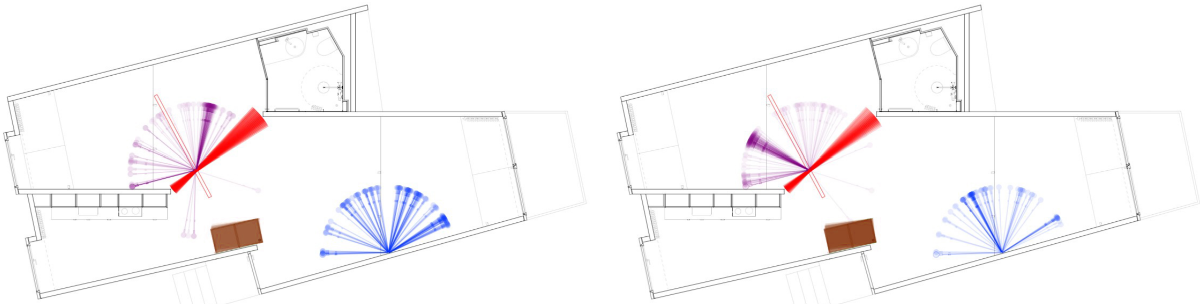


Figure 3: *The spatial mapping of probability distributions shows all states that fulfill certain filter criteria, as defined in Section 4.3. Here, we see events at which the rotatable wall is rotated between 72 and 88 degrees while the rotatable closet was between 0 and 8 degrees per group. Left: the group of test-subjects aged 18-45, and right: aged 45-70. The probability distribution is calculated based on the frequency of usage.*

more specific information about sensors can be *looked up*, including precise sensor readings and temporal animations of individual sensors. In this task, data is *consumed* to *present* individual values.

T3: Investigate Differences among User Groups (R3) To *explore* behavioral differences and similarities between user groups in the context of test subject information, the main view incorporates *comparisons* of two subject-groups, either by side-by-side view of the same visualization (small multiples) or by direct comparison in the same visualization. Interactivity is important for exploration.

4.1. Spatial and Temporal Aggregation (T1)

A central research questions is *how* rotatable elements are used by whom, individually and in conjunction. In order to translate the individual measurements to physical constellations of rotatable elements, we visualize the elements in their spatial context on a floor plan. However, the sensor data is too complex to be visualized directly. Hence, we use an overview and detail approach. For this, we aggregate the spatial and temporal information.

Spatial Mapping of Probability Distribution To spatially map the measurements, we draw the corresponding elements of the selected group on the floor plan, see Figure 3. The opacity of the elements is determined by the probability of a certain configuration and is normalized with respect to the selected subset. The colors are chosen consistently throughout all visualizations in order to establish correspondence: the rotatable wall is red, the rotatable closet is brown, lamp A (on the rotatable wall) is purple, and lamp B (on the building wall) is blue. Through this visual representation of states of all rotatable elements, we learn more about the spatial relations of the elements and how they define space. This visualization is designed to show the spatial distributions of one time range at a time. Comparing multiple time ranges (or sets of test subjects) is supported by a side-by-side view (juxtaposition) of two instances of this visualization. Later below, we introduce a visualization specifically aiming for comparisons on the same floor plan.

Temporal Aggregation in Timeline Control In order to guide the user in the selection of a time span of interest, we provide a timeline control, shown in Figure 4 (bottom), which maps the quantitative time attribute to the spatial x-axis and allows the user

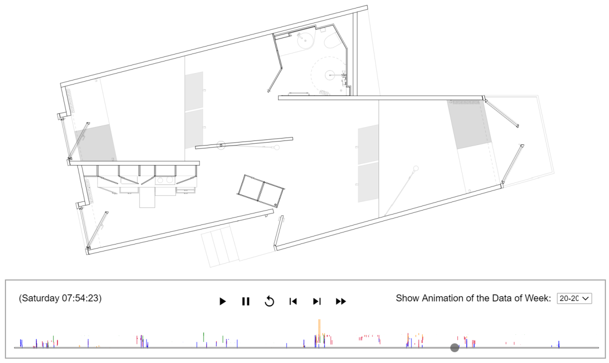


Figure 4: *Visualization of the element state in the apartment on Saturday at 07:54:23 (hour:min:sec) of week 20 in year 2020, displaying the configuration of the rotatable elements (wall, closest and lamps). Below, a histogram provides a temporal overview for the occurrence of events within the selected week.*

to move ahead to specific points in time using a slider. Above the slider, we placed an activity line chart. Vertical lines colored by hue according to the categorical rotatable elements indicate a rotation of the corresponding element. The size of the movement is expressed by the height of the line. This chart provides a temporal overview, so that the user is aware when a rotatable element is moved, and can thus move ahead to that point. The design of the slider closely follows scented widgets [WHA07], which aim to augment well-established UI elements with visual encodings.

4.2. Detail Animation of Configurations (T2)

To convey the temporal evolution of events throughout a day or a week, the aforementioned timeline control was added below the floor plan of the Mock-up, which is shown in Figure 4 (top). On the floor plan, the four rotatable elements (wall, closet, lamp A, and lamp B) are rotated exactly between the angles and with the duration measured by the sensors. For context, other movable elements are displayed as well, including opening and closing doors, windows, hoppers, and drawers, which have been equipped with on/off sensors that were evaluated separately. The user can select the week to be animated. Animations can be sped-up, paused or restarted.

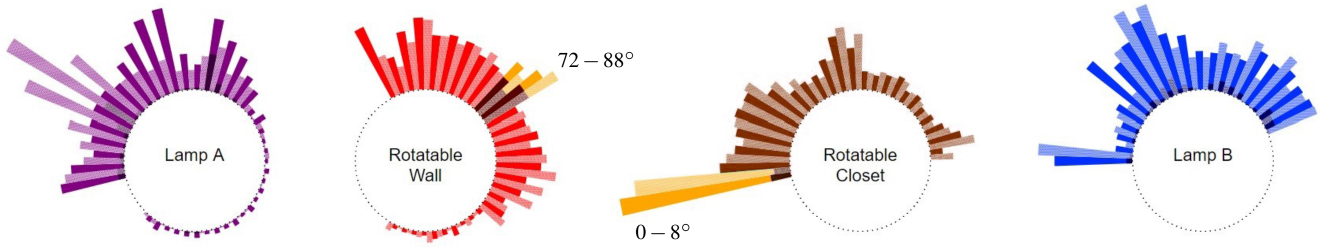


Figure 5: *The double grouped radial histogram visualizes the angular distribution of rotatable elements, in this case for frequency of use. From left to right: lamp A, rotatable wall, closet, lamp B. The orange color highlights the selected bars. In this example, the bars at angles 72-88 for the wall and 0-8 for the closet are selected. In dark, the inner histogram is visible. The dark bars are the bars of Group 1 with test subjects aged 18-45, and the light bars are the bars of Group 2 with test subjects aged 45-70.*

4.3. Interactive Filtering and Exploration (T3)

Filters For data exploration, we include filters to define subject groups. This creates a *coordinated view* that makes changes in one view affect other views [BWK00, Sch08].

Radial Distribution of Angles Since the spatial orientation is given by angles, the data naturally lends itself to a radial layout. Draper [DLR09] presented a survey on different radial spatial arrangements and encodings. We introduce a radial histogram that serves three roles: it acts as a control element, it shows the distribution of frequency and duration of states for every rotatable element, and it shows information about spatial relationships between them. To convey the orientation of an element visually, we aligned the rotation angles of the rotatable elements with the corresponding sections on a circle. The distance from the center shows either the frequency of states, i.e., how often the element was moved *to* a given angle or the duration of states, i.e., how long the element remained at the given angle. To add comparisons of the usage of the element at different orientations, we chose a grouped histogram design. The two groups can be distinguished by their fill: the bars of the first group are filled with a solid color and the bars of the second group are textured with a lighter shade of the same color. Since the subject-group size and therefore the amount of data can be different, the histogram can be viewed with absolute or relative scale. The latter facilitates comparison of the subject-groups. The scale is global over all four radial histograms. Additionally, the bin size is adaptive and can change with user input. Upon selection of bars through a mouse-click, all time points are selected in which the rotatable elements are in one of the selected states. It is then interesting to see, how the state of all other rotatable elements correlates with the selected states. The distribution of the other elements is thereby conditioned on the selection, resulting in another histogram to be visualized. Figure 5 shows the two radial histograms together. We refer to them as the *outer* and the *inner* histograms. The *outer* histogram is what is visible from the beginning and shows the frequency/duration of the complete set of states. It is fixed, unless new filters are applied. The *inner* histogram shows the frequency/duration of the subset of states defined by the selection of bars. It is laid over the outer histogram and its bars can be distinguished by color, with the inner bars being darker. A tooltip provides exact angles, frequency and duration for both histograms. The histogram is coordinated with the spatial mapping of the probability distribution, which draws the inner histogram on the floor plan, see Figures 3 and 5. By aligning the zero-degree orientation in the histogram with the floor plan and using the same color, the two components are visually linked.

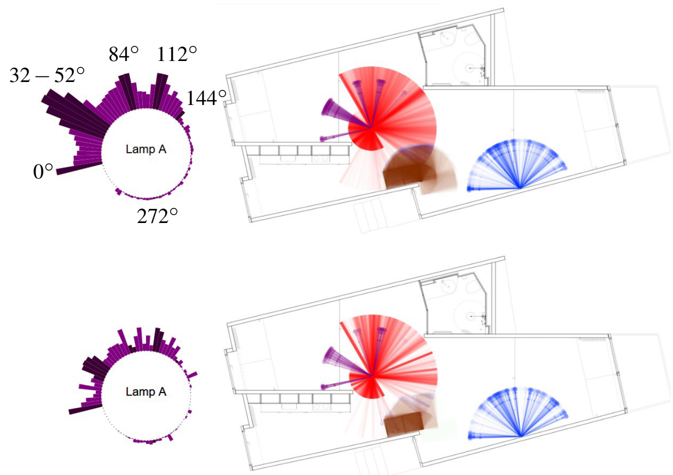


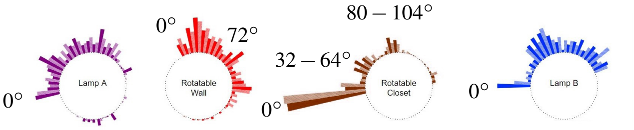
Figure 6: *Radial histogram of lamp A for frequency of states (top) and duration of states (bottom) for all test subjects. In both histograms, the bars at degrees 0,32-52,84-92,112-120, 144 and 272 are selected and the resulting spatial mapping is shown.*

5. Case Studies

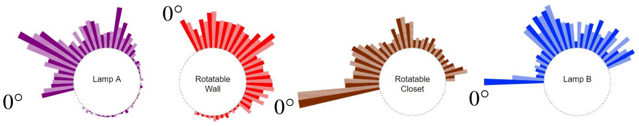
Next, we show qualitative results and report selected observations made based on the visualizations in the form of anecdotal evidence. Note that all observations are with respect to the test subjects who participated in the study. Details on challenges related to data collection are provided later in Section 6.2.

5.1. Observation on Individual Rotatable Element

Lamp A was rarely used in the living area. Instead, it was mostly used in the bed area. Figure 6 shows the radial histogram for lamp A for duration and frequency of states. Consider the bottom histogram for duration of states. Evidently, there are few bars for angles at 144 – 272 degrees, indicating that the lamp was rarely used in those states. By looking at the spatial mapping shown on the right of the figure, we can see that in those states lamp A was rotated to the living area. Additionally, both the histograms on duration and



(a) *Radial Histograms for duration of states and relative scale.*



(b) *Radial Histograms for frequency of states and relative scale.*

Figure 7: *Double grouped radial histograms for singles and pairs. Left to right: lamp A, rotatable wall, rotatable closet and lamp B.*

frequency of states shows that lamp A was most often rotated to and positioned at $32-52$ degrees, which places the lamp in the bedroom area. Other common angles were $84-92$ and $112-120$ degrees, for which the lamp was located in front of the bathroom.

5.2. Comparisons between User Groups

Next, we list observations that were made about single and two-person households. For this, we set *Group 1* to *single* and *Group 2* to *pairs*. We refer to the two subject-groups as G1 and G2, respectively. From the parallel set of the current data, we read that G1 contains 24 and G2 contains 68 individual test subjects. Thus, there are 24 and 34 weeks worth of sensor data for G1 and G2, respectively.

Despite frequent rotations of the closet, both groups used it mostly in one of three states. Figure 7a shows the double grouped radial histograms of the four rotatable elements for *duration* of states and relative scale. The bars of G1 are solid and the bars G2 are textured in a brighter shade. We focus on the rotatable closet (brown). There are three states in which the closet was found to be used in most often: $0-16$, $32-64$ and and $80-104$ degrees. The first state was preferred most often. A possible explanation is that ordinary non-rotatable closets and other large and heavy objects are usually placed to walls, to not unnecessarily take up open space since they are not easily moved out of the way. Having the closet rotated to the wall (0 degrees) and out of the way might be conscious. Additionally, we can observe that the closet was rarely rotated more than 90 degrees. One reason for this can be found when looking at the spatial mapping to see the states at those angles. After selecting any bar over 90 degrees, the closet intentionally blocks the entrance. An interesting finding is that the architectural idea of deliberately creating intimacy by concealing the front door was rarely used by the participants. Figure 7b shows the double grouped radial histograms of the four rotatable elements for *frequency* of states and relative scale. We can observe that the frequency of use at $16-64$ degrees did not differ much from the frequency of use at $80-104$ degrees and was nearly only half of the frequency at 0 degrees. This implies that despite the closet being moved often and mostly only between 0 and 104 degrees, it was left in just three possible states. As learnt from the inhabitants' questionnaire feedback, one possible reason is the design of the closet, which is composed of two separate compartments. One is opened from the front and the other from the back, see Figure 1c. It is necessary to rotate the closet by at least 30 degrees, to reach the back door, explaining the higher frequency of use for less than 90 degrees. Another reason is the spatial impact of the rotated closet, since opened to 90 degrees, it is visually separating the living area from the kitchen area. In conclusion, the radial histogram of the rotatable closet reflects its usability and intent.

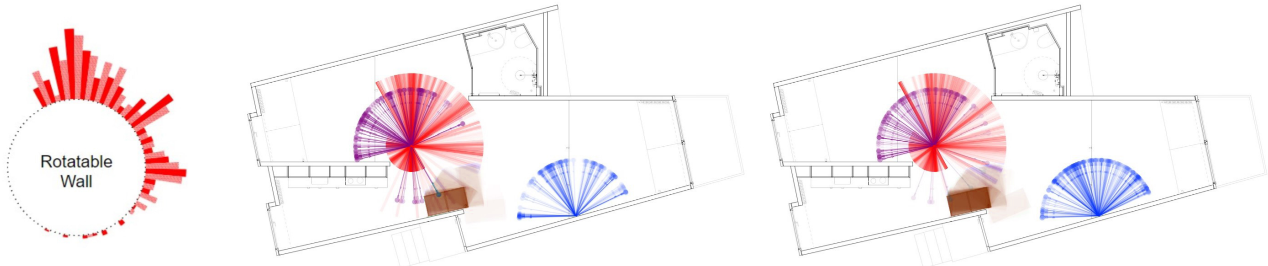
The two groups G1 and G2 used the walls similarly in the morning (06:00-09:00), but differently in the evening (21:00 - 23:59). Figs. 8a and 8b show the radial histograms for the rotatable wall and the spatial mappings for duration of states and with relative scale between 06:00-09:00 and 21:00-23:59, respectively. For the histogram in the evening, we see that both groups have different states that were used longest. We select all bars and take a look at the spatial mapping. Figure 8a shows the states of the wall for G1 and G2 in the morning. It is apparent from the spatial mapping that the wall was not used significantly different by the two groups. This is not the case in the evening. Figure 8b shows the states of the wall for G1 in the evening, which is at an angle that creates a separation of the bed area from the living area and kitchen (angles 72-88). In contrast, G2 mostly has the wall at a position, so that it is perpendicular to the bed podium (angle 96-128). It does not fully close off an area and instead takes up much of the room in the living area, particularly forcing a longer path to move between the kitchen and bathroom. This could possibly indicate that when one person was already in bed, the wall was chosen at this position in order to separate visually the bed area from the other areas but in such a way that the second person outside the bed area still had access to the bathroom without having to rotate the wall. Another explanation it the wish to hide the sleeping area while having guests without blocking the way to the bathroom, as was indicated in questionnaire responses. These observations are interesting as they can indicate different behaviors due to the number of occupants in a home. Especially for pairs or while having guests, we may be able to find use of the wall that can be linked to behavior of individuals motivated by consideration for the partner or guest.

6. Discussion

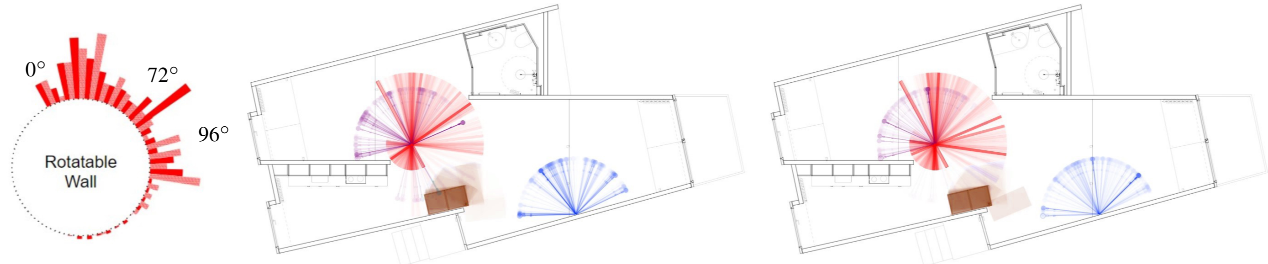
Next, we report the feedback of the collaborating architecture researchers, and we reflect on the challenges faced in the collection, interpretation, and use of sensor data in performative architecture. Afterwards, we discuss avenues for future work.

6.1. Informal Feedback

For architecture researchers, the study has provided interesting insights – not only into how rotatable elements are used, but also into how they can be further developed. The most popular positions of the revolving wall are those anticipated by the architecture researchers, for example to separate the spaces. The architecture researchers noted that the sensor data visualization was an effective tool to identify calibration errors, which enabled an improvement of the data quality. Finally, the visual analysis of sensor measurements of rotatable elements in the context of filterable test subject groups revealed new insights on usage preferences, patterns and differences. The different use of one-person and two-person households as well as those between the sexes and ages are surprising and constitutes a new insight that can spur further research in architecture.



(a) *Spatial mapping for time span from 06:00 to 09:00. For the group of single test subjects (left) and pairs of test subjects (right).*



(b) *Spatial mapping for time span from 21:00 to 23:59. For the group of single test subjects (left) and pairs of test subjects (right).*

Figure 8: *Radial histogram for the rotatable wall and the spatial mapping. Here, Group 1 contains single test subjects (left) and Group 2 pairs of test subjects (right). The sensor data is further filtered to only include states between 06:00 to 09:00 (top) or 21:00 to 23:59 (bottom).*

6.2. Challenges and Limitations

One challenge is the lack of data collected per test subject. A study by Gardner et al. [GLW12] on the psychology of making health habitual suggested that it takes an average of 66 days, before new behavior becomes automatic. While this observation might not directly translate to living behavior, it is clear that after one week long-term habits have not formed yet. However, the architecture researchers did not aim to study long term habits, but behavioral tendencies instead to obtain a first overview of the usage, measurement and evaluation of rotatable elements. Another related challenge is the distribution of the test subjects. Despite precise selection through different media, we found that the majority of test subjects had a higher education and an affinity with architecture. For example it turned out that many of the test subjects with an age between $18-30$ years were architecture students, limiting the observations to this cohort in their age group. The background of the test subjects may have had an impact on how movable elements were used. In addition, the test subjects did know about the sensors and that measurements were taken respectively that they were being observed through interacting with the environment. Allowing guests into the apartment encouraged the inhabitants to demonstrate the movement of elements. While it was possible to filter time ranges when guests were present, there is no guarantee that the every arriving guest was accounted for in the reports manually filled out by the inhabitants. Further, test subjects older than 60 years were more difficult to recruit during the global pandemic. Another limitation is the temporal analysis of the time series, which was limited to linear positional encodings and temporal animations. The detection of patterns and trends can be supported better by utilization of similarity metrics [VJC09] or more sophisticated filter queries [AAA*21].

7. Conclusions

How and when rotatable space-defining elements are used by inhabitants to adjust their living space remained an interesting open research question in architecture. In this paper, we built an interactive visual analysis tool for the exploration of the multivariate time-series data collected for rotatable elements in a prototype apartment, allowing architecture researchers to gain insight on the use of rotatable elements, development of usage over time, spatial relationships between elements and trace of inhabitants for specific aspects of the data. We utilized radial histograms to both display the preferential placements of rotatable elements and to filter co-occuring element constellations. To support comparisons of user groups, the grouped radial histograms showed two radial bars next to each other. Animations further support the temporal exploration of rotations. Using the visual analysis tool, we reported on selected observations made by the architecture researchers regarding the preferred placement of a rotatable lamp, the three preferred placements of a rotatable closet, and lastly the differences in wall rotations among single-person and two-person households.

In the future, similarities of weekly usage patterns could be further emphasized [VJC09] and more query operations could be offered to filter time spans with co-occurring sensor activities [AAA*21]. Since all sensors have a spatial reference in the floor plan, the embedding of the data visualization in the physical space could be valuable [WJD17]. Further, we limited the user group of the visualizations to the architecture researchers. On the other hand, the inhabitants could learn about their own habits and might want to adjust them. Personal visual analytics is a discipline concentrating on the awareness of own personal data with the purpose of self-reflection [HTAA*15, ABGG21].

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