Spatiotemporal Analysis of Sensor Logs using Growth Ring Maps

Peter Bak, *Member, IEEE*, Florian Mansmann, *Member, IEEE*, Halldor Janetzko, and Daniel A. Keim, *Member, IEEE*

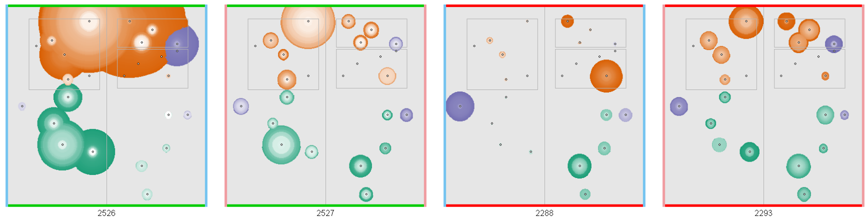


Fig. 1. *Growth Ring Maps* allow analysts to find similarities and extract patterns of interest in spatiotemporal data.

Abstract—Spatiotemporal analysis of sensor logs is a challenging research field due to three facts: a) traditional two-dimensional maps do not support multiple events to occur at the same spatial location, b) three-dimensional solutions introduce ambiguity and are hard to navigate, and c) map distortions to solve the overlap problem are unfamiliar to most users. This paper introduces a novel approach to represent spatial data changing over time by plotting a number of non-overlapping pixels, close to the sensor positions in a map. Thereby, we encode the amount of time that a subject spent at a particular sensor to the number of plotted pixels. Color is used in a twofold manner; while distinct colors distinguish between sensor nodes in different regions, the colors' intensity is used as an indicator to the temporal property of the subjects' activity. The resulting visualization technique, called Growth Ring Maps, enables users to find similarities and extract patterns of interest in spatiotemporal data by using humans' perceptual abilities. We demonstrate the newly introduced technique on a dataset that shows the behavior of healthy and Alzheimer transgenic, male and female mice. We motivate the new technique by showing that the temporal analysis based on hierarchical clustering and the spatial analysis based on transition matrices only reveal limited results. Results and findings are cross-validated using multidimensional scaling. While the focus of this paper is to apply our visualization for monitoring animal behavior, the technique is also applicable for analyzing data, such as packet tracing, geographic monitoring of sales development, or mobile phone capacity planning.

Index Terms—spatiotemporal visualization, visual analytics, animal behavior, dense pixel displays.

1 Introduction

Spatiotemporal visualization is a challenging research field. While traditional two-dimensional maps are familiar to most users, extending their representation to more than three dimensions (position x & y, color) becomes a real challenge. Recent research proposed to use the third spatial dimension to represent time, but thereby introduce new usage challenges, such as the ambiguous position of a point in a 3D representation when viewed on an ordinary computer screen. Alternatively, distortion of the geographic dimension to create space for otherwise overlapping data points was proposed. However, recognizing geographic entities after non-linear transformations of both shape and size challenges viewers. [5]

Depending on the granularity of the measurements and the considered time span, large amounts of data are collected when monitoring movement. In the scope of this paper, we analyze RFID sensor data of the movement of 83 mice in a large cage over a time period of several months resulting in a dataset of several hundred Megabytes. Thereby, the principal research question is whether there is a significant difference between movement patterns of wildtype, which are healthy mice, and Alzheimer-transgenic mice, which carry the Alzheimer disease.

Figure 2 shows the multi-level cage used in the mice experiment. It is equipped with 27 strategically placed RFID receptors that log mice activity when they come closer than 3 centimeters to the receptors. This kind of logging results in discontinuous event data, which can then be used to approximate lower bound properties of the actual movement since more detailed data is unavailable.

In this paper, we systematically analyze the mice movement data set: First, we consider the temporal aspect of mice movement. Thereby, we model the data by calculating the average daily movement pattern. This is done by summing up the lower bound distances per hour. Clustering this data shows that most female Alzheimer transgenic mice end up in the same cluster, thus revealing similar data properties. Second, in order to assess the spatial component of the data, we consider the movement between sensors in a matrix representation of the sensors. For each of the four groups of mice (male vs. female and healthy vs. Alzheimer transgenic) such a matrix representation is drawn. Unfortunately, only considering the spatial information in this representation does not sufficiently help us to gain insight into differences in the movement behavior of the mice groups. Third, only the proposed *Growth Ring Maps*, which are the main contribution of this paper, take the full spatiotemporal information of the dataset into account and reveal detailed movement behavior of individual mice and mice groups, examples are shown in Figure 1. To cross validate these results, we use a multi dimensional scaling (MDS) approach on the same feature vectors, which are used for generating the Growth Ring Maps.

The paper is organized as follows: Section 2 discusses related work in the field of spatiotemporal data visualization. Afterwards, Section 3 presents a clustering approach on the temporal information, followed by Section 4, which analyzes the data using only spatial information. Next, Section 5 introduces our novel visualization approach on spatiotemporal data, which is validated using MDS. Finally, Section 6 concludes our work by summarizing our results, contributions, and future work.

- *Peter Bak is with University of Konstanz, E-mail: bak@dbvis.inf.uni-konstanz.de.*
- *Florian Mansmann is with University of Konstanz, E-mail: mansmann@dbvis.inf.uni-konstanz.de.*
- *Halldor Janetzko is with University of Konstanz, E-mail: janetzko@dbvis.inf.uni-konstanz.de.*
- *Daniel A. Keim is with University of Konstanz, E-mail: keim@dbvis.inf.uni-konstanz.de.*

Fig. 2. Cage of the mice experiment equipped with 27 RFID receptors. ©Department of Behavioural Biology, University of Muenster, Germany.

2 Related work

2.1 Animal Movement

The analysis of animal behavior is an important part in biology research. In many cases a human observer has to note each movement and social interaction with other animals. Therefore, it is a very time consuming and expensive undertaking to create a correct and accurate log. A simple way to reduce costs is an automatic detection of animal movements (in this special case of cows) proposed in [8]. This work introduces a local positioning system based on triangulation via radar, which provides continuous data and up to 50 centimeter accuracy. The disadvantage of using radar technology is a reduced accuracy near metal objects like cattle troughs or feeding grounds. Since most of the interactions between cows are at these sites, an automatic way of finding social interactions failed.

A real-time playback of recorded mice movements using RFID technology is proposed in [17]. The receptors were placed at important locations in the cage, i.e., watering places or ends of tubes or ropes. These sensors were triggered whenever a mouse came nearer than 3 centimeters. We are using the same records as analyzed in this publication.

Many experiments deal with effects of the Alzheimers's disease on mice and their bevavioral pattern. Effects of environmental enrichment on exploration and memory on transgenic female mice are analyzed in [7]. It shows that environmental enrichment increases only exploratory behavior and has no clear influence on learning and memory performance.

The study in [18] deals with transgenic Alzheimer mice in semi-naturalistic environments and examines the behavioral differences between wildtype and transgenic mice. Though transgenic mice in semi-naturalistic environments have more plaque than transgenic mice in standard cages, they could not be differentiated from wildtype mice by their behavior pattern. As our data are fetched in a semi-naturalistic environment, we have to keep in mind that it will be difficult to separate wildtype and transgenic mice.

2.2 Temporal and Spatial Analysis

There are many techniques dealing with visualizing time series data. The *TimeWheel* technique proposed in [21], for example, visualizes time-dependent multivariate data. It places a time axis in the middle of the screen and all other dimensions are positioned circularly around the time axis. For each data item lines are drawn from the corresponding point on the time axis to the points on the other axes.

One fundamental work in the field of time series analysis is Hochheiser and Shneiderman's *Time Searcher*, which uses traditional line graphs [10]. The tool's focus is set on the dynamic query interface. Through rectangular boxes, the user can simultaneously specify ranges of values and time intervals to find matching time series. Furthermore, the innovative user interface of the tool is characterized by a query-by-example interface, support for queries over multiple time-varying attributes, query manipulation, pattern inversion, similarity search capabilites, and graphical bookmarks.

Visualizing periodic time series can also be achieved by using a SpiralGraph [4]. This approach arranges each data item spirally, whereas the curvature of the spiral is adjusted to the periodicity of the data.

Our first consideration was to apply pixel visualization techniques like the *Recursive Pattern* approach [14]. This technique enables visualizing recursive occurring patterns with known periodicities, e.g. weekly or monthly patterns. The screen filling property of Recursive Patterns make them applicable for long time series. However, it is difficult to transfer this approach into a geospatial analysis setting.

Other application scenarios deal with the problem of finding usage patterns and visualizing them on larger time scales. Van Wijk and van Selow, for example, combined a clustering algorithm and a calendar view to identify daily energy consumption patterns [24]. Their presented methods provide insight into the dataset and are suitable for fine-tuning their model's parameters to predict future energy consumption. Our temporal analysis approach is similar to this approach since we also use a clustering method to analyze sets of temporal distributions, which in our case is individual movement of mice over time. However, it differs since a) we analyze averaged daily movement patterns rather than usage patterns over several months and b) we use hierarchical clustering to avoid definition of clustering parameters based on prior knowledge of the data sets.

Many visualization approaches stick with the map metaphor and visualize small charts on top of it. One such approach shows thumbnails of temperature variation over time on top of a geographic map [20]. The thumbnails are generated using the proposed two-tone pseudo coloring scheme, which is capable of encoding time series data in a space-efficient way.

The Lexis Pencil approach [3], as another example, creates colored pencil-like glyphs to encode multi-variate data with time references. In [22], these objects are placed at their geospatial positions on a map, which facilitates displaying of several time series at one geographical position.

Another concept of visualizing geo-temporal information is animation. While this concept is widely used for monitoring office buildings, it is very time-consuming and neither scalable to a large number of moving objects nor to large time spans. In order to compensate for these drawbacks, their techniques use a combination of animated maps, a time-sensor-matrix, and video sequences to analyze the history of living spaces [11]. Using the matrix, users of their system can identify movement patterns in large time series and then track it using the linked map and video sequences.

A further popular visualization option for spatiotemporal data is the use of three-dimensional scenes. The studies [16, 13], for example, use a two dimensional map and add time as the third dimension on top to display events with references in space and time. Moving objects will thereby result in ascending lines. However, overlap, ambiguity, and low scalability make it nearly impossible to use this method for a large number of mice in a time span of eight months.

Visualizing huge data sets is a challenging research area and many approaches have been proposed. Bertini [1] for example allows the user to examine small data items in detail, avoiding a loss of information in low-density areas while reducing over-plotting in high-density areas. Ellis [6] uses auto-sampling to reduce the over-plotting in parallel coordinates and scatter plots. Similarly, Ward et al. [12] uses hierarchical clustering techniques [26] to reduce clutter in several visualizations in the system.

A well known technique for visualizing points in a two dimensional space being at the same position is using pixel placement approaches. They are used in arbitrary applications like the visualization of geospatial point sets [19] or the pixel bar chart technique [15]. The idea behind these techniques is to show all data points without overlap

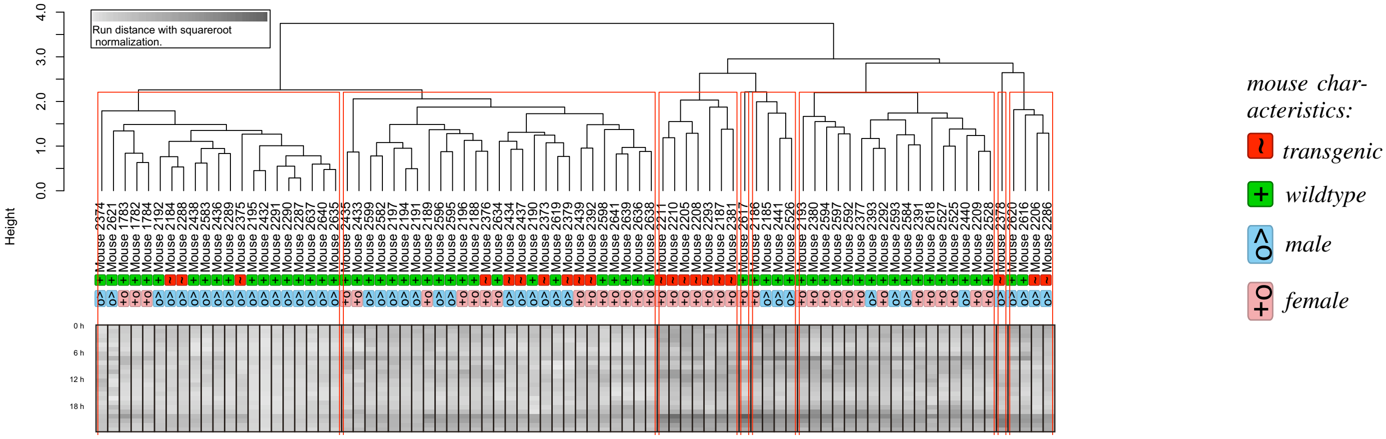


Fig. 3. Hierarchical clustering of the averaged daily movement patterns of each mouse. We first normalized the activity patterns with a square root function and then hierarchically clustered the resulting feature vectors using average linkage.

while each point should be moved not more than necessary. Therefore we used this approach in order to show all sensor triggerings over the whole life span of a mouse.

3 Temporal analysis using Hierarchical Clustering

To motivate temporal analysis of mice movement we wanted to verify the hypothesis whether it is possible to distinguish between Alzheimer-transgenic and wildtype mice based on the amount of movement hourly aggregated over the days they spent in the cage. Since our test setup used RFID-sensors and receptors to track mice movement, we were only capable of measuring discrete positional data for each mouse when it approaches the strategically placed receptor nodes, such as watering places or passages from one compartment of the cage to the next one.

In order to estimate the distance that each mouse traveled in a particular time interval, we calculate the distances between all pairs of sensor nodes and then infer a lower bound of the actual mouse movement. Note that this does not take the fact into account that mice can move freely in the cage without being tracked when they avoid coming close to the receptor nodes. However, due to the high number of receptor nodes (27 nodes) and due to the long duration time of the experiment (8 months), we believe that this lower bound estimation characteristically reflects the activity patterns of the mice.

By applying square-root normalization between 0 and 1, we compensate for the fact that most aggregated distances were quite similar except for a few outliers. The Manhattan distance is the method of choice to pair-wisely compare the 24 dimensional feature vectors; it sums up the absolute difference of movement for each one hour time interval.

Most clustering algorithms require a pre-defined set of parameters, such as the number of clusters, the minimum density of a cluster, etc. However, these temporal movement patterns have no intrinsic pre-known cluster structure that we could use to define these parameters. This results in the choice of a hierarchical clustering method. Hierarchical clustering methods visually represent a tree of distances between data points and clusters by subsequently joining the two elements with the least distance in each step [25]. While single linkage methods use the minimum distance between the closest data point in the cluster to the new data point or cluster, complete linkage methods use the maximum distance between the set of points in the first cluster and the set of points in the next cluster. The employed average linkage clustering can be seen as a compromise between the sensitive complete linkage clustering and the single-link clustering, which tends to form long chains of data points rather than compact clusters. Applying this method results in the cluster dendrogram shown in Figure 3, which shows the average linkage distance different mice and clusters in a tree visualization. Afterwards, the cut-off point for the cluster definition is manually fine-tuned based on the cluster dendrogram resulting in eight clusters (colored red) for the distance of 2.5.

The resulting clusters reveal one cluster (3rd from the left) consisting of only transgenic female mice. Furthermore, the 4th, 5th and 6th clusters contained only wildtype mice. It was interesting to see that while the 3rd cluster included most female transgenic mice, we were not able to cluster the transgenic male mice based on the amount of their daily movement. After presenting this result to the experts, they stated that this is possibly due the fact that male mice stay in one territory and defend it against other male mice while female mice are less restricted in their movement between the different compartments in the cage. Therefore, movement patterns of male mice are much more restricted and subject to less variation.

4 Spatial analysis using Transition Matrices

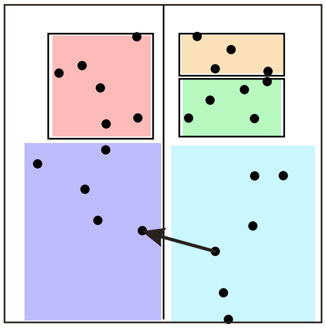
In parallel to the temporal analysis we conducted a spatial analysis of the underlying data. The aim of this type of analysis is to capture the territorial behavior of mice independent of time since this aspect will be covered in the spatiotemporal analysis. Ideally, this spatial analysis should reveal significant differences between movement profiles of transgenic/wildtype and male/female mice. Also, the created profiles should help to understand the effects of Alzheimer on territoriality.

In order to create movement profiles of the mice, the spatial information of the sensors and the direct sequence of moving from one sensor to the next one were used. A sensor matrix was created to visualize this kind of movement. As the first step, the 27 sensors of the cage were grouped into the 5 levels/compartments of the cage. Whereas different compartments represent a more-or-less closed space, it was still possible to move from one compartments to the other. Figure 4(a) shows the areas and the sensors by different colors. The second step in creating the sensor matrix was to map the spatial location of the sensors to a linear representation. This is done by manually ordering the nodes in a way that minimizes distances between adjacent sensor nodes while being constrained by the previously introduced grouping.

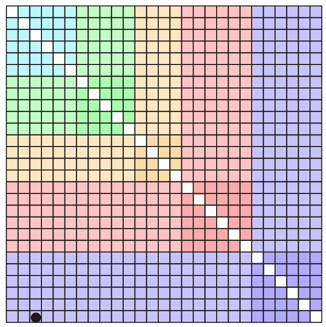
The matrix was then designed as the cross product of the linear arrangement of sensor nodes. A directed movement from one sensor to another is mapped as the corresponding cell in the matrix. Figure 4(b) shows the created sensor matrix, in which the colors correspond to the areas of the cage. The diagonal line was left out from the analysis, because multiple triggering of the same sensor was cleaned out from the data during preprocessing.

The analysis of movement was carried out using these sensor-matrices. One sensor matrix was computed for combining wildtype or transgenic, and male or female mice, while the movements were aggregated over the whole time period, consequently resulting in four different matrices. The number of occurrences of a movement pattern were mapped to the intensity of the grayscale color map.

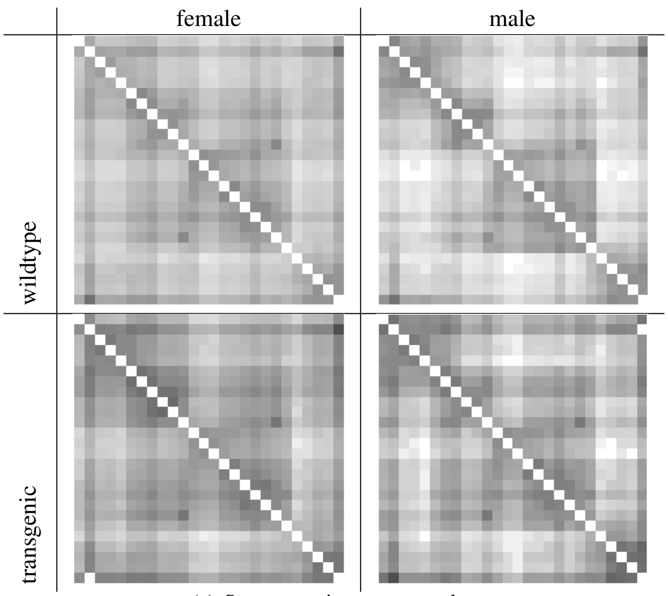
The results of this technique are shown in Figure 4(c) presenting wildtype (upper row) and transgenic (lower row) mice for their whole



(a) Multi-level cage



(b) Sensor matrix



(c) Sensor matrix per mouse class

Fig. 4. Sensor matrix visualization to capture movement between sensor nodes. a) 2D projection of the multi-level cage. b) The sensor nodes are grouped according to levels (color-coded) and then manually rearrange to minimize distances between neighboring nodes. Note that the movement between sensor 3 and 27 (arrow in a)) is indicated with black to illustrate the meaning of the matrix. c) The spatial movement profiles of mouse groups are then represented in gray-scale sensor-matrices (bright colors = low movement, dark color = high movement). The first row shows wildtype, lower row shows transgenic mice, whereas the left column shows female and the right column male mice.

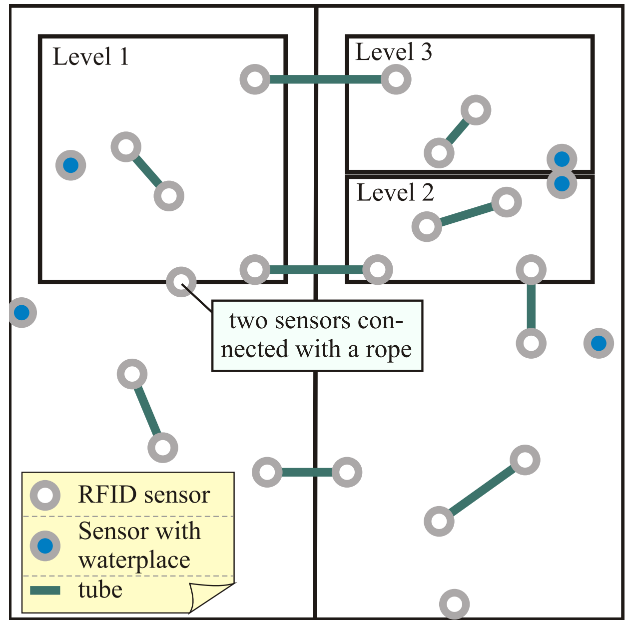


Fig. 5. Schematic example of the cage showing regular locations and water places. Higher level locations were mapped using a separation border. Direct connections through a tube are highlighted by connecting lines.

lifespan. The left column represents female and the right male mice. In order to extract behavioral differences, a visual comparison can be carried out by looking for distinguishing patterns between the sensor-matrices. Visually salient is the behavior pattern of male-wildtype mice. Their movements are likely to occur in the same compartments, as indicated by the concentration of frequent movements along the diagonal line of the matrix. Such territoriality is absent for female, and is also less evident for male-transgenic mice.

However, these interpretations are blurred by the sensitivity of the method to noise, its dependence on the order of the sensors, and the high aggregation level of the data. As a result, the differences between wildtype and transgenic mice reveal only limited opportunities for analysis. Further steps are needed to make the requested information visible to users.

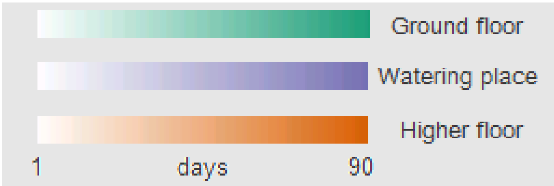
5 Spatiotemporal analysis using Growth Ring Maps

Since neither the temporal nor the spatial analysis alone can reveal the behavioral differences of wildtype/transgenic and male/female mice, we extended our analysis to combine these analytic aspects into one framework. For this purpose, we introduce an new technique called *Growth Ring Maps* for visualizing spatiotemporal data from sensor logs. Behavior, as described previously, is assessed by logging mice's visits at sensor in the cage. The behavioral properties that have to be taken into account are the spatial information (where the sensors are located) with different semantic type of sensors, the temporal aspects (when a sensor was visited) and number of visits at a sensor.

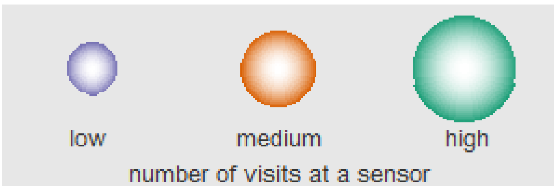
To assess spatial properties of mice's behavior, the location of the sensors was mapped to screen coordinates, keeping the relative location of the sensors at their approximate position. Note that this 2D projection of the cage presented in Figure 5 is actually a simplification of the 3D cage design shown in Figure 2. However, this projection was possible since the sensors in the original cage were placed in a way that they do not overlap in the vertical projection. There are some important semantic differences between locations, such as water places and regular locations, whereby the latter ones can be further divided into ground floor and higher floor locations. These three semantic properties were mapped to colors using ColorBrewer's three-level qualitative color schema [9]. Water places were mapped to blue, ground floor locations to green and higher floor locations to orange, as shown in Figure 6(a). The number of colors can be increased, when more semantic properties are of interest.

Temporal properties of mice's behavior were assessed by the days, at which particular sensors were visited. This property was mapped to the sensors' color gradients. Light colors indicate early dates and intense colors indicate later days of visits, as shown in Figure 6(a). For reducing noise, we limited the number of days to the first 90 days of mice's life in the cage. This seems convenient, since the average life expectancy of a wildtype mouse was 86.6-days (StDev=48.1), of transgenic mice 79.3-days (StDev=29.6). The selected time period can be further extended or limited by adjusting the intervals of the color gradients.

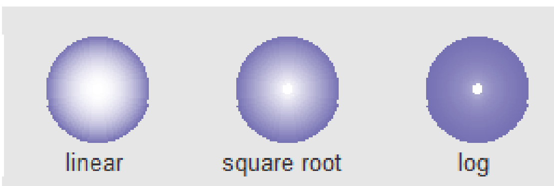
For assessing the number of visits at a particular sensor in a visual way, we used an orbital pixel placement technique resulting in *Growth Ring Maps*. Visits at a particular sensor were mapped by drawing single pixels – one for each visit – in a circular layout around the sensor's location. Sensors with visits less than 20% of the maximum number of visits at a sensor were disregarded for reducing noise in the representation. The color of drawn pixels was determined by the sensors'



(a) Colors show sensors' semantic properties and color gradient shows the time of visits.



(b) Visits at a sensor are mapped by pixels, placed in a circular layout around the sensors location. Larger circles indicate higher number, and smaller circles lower number of visits.



(c) Scaling of the color gradients can applied to enhance different time points of visits. Square root scaling is used to provide equal weights to all time points.

Fig. 6. Spatial properties of mice behavior are mapped to color hue, temporal properties to its brightness (a), number of visits to a circular layout (b), which result in an expressive visual picture that can be scaled to enhance different time periods (c).

semantic property and the color gradient by the day of the visit. The pixels were sorted by day, resulting in a continuous gradual map having bright colors in the inner, and intense colors at the outer Growth Rings. The size of the layout indicates the overall number of visits at the sensor. Figure 6(b) schematically shows few (625), medium (1250) and many (2500) visits.

When creating Growth Rings for positions closely located to each other, new overlapping positions or interlacing Growth Rings could occur. During the growth phase the technique always looks for free positions in a concentric manner, as close as possible to the center. Consequently, when two or more Growth Rings would start overlapping or interlacing, free positions will be only available in all the other directions giving precedence to earlier growth phases. Therefore, overlapping and interlacing Growth Rings are avoided.

Due to the concentric mapping, rings with equal width, in the outer rings (towards the end of the time period) have greater area-size, and therefore are visually more salient than inner rings (beginning of the time period). In order to show how to counterbalance this effect by sclaing, we conducted a mapping using a time period of 100 days having 25 visits everyday (resulting in 2500 pixels with equal distribution of color intensity)by different scaling functions, as shown in Figure 6(c). Linear scaling of the gradients enhances the bright colors in the inner Growth Rings, due to the more compact representation of the bright pixels. Logarithmic scaling enhances intensive colors at the outer Growth Rings. Square root scaling shows a homogeneous smooth gradient of color intensity by equal distribution and should therefore be applied to overcome the bias inherent to the pixel placement method. Additional optional scaling can be used on the color-gradient, in order to enhance different features in the distribution of the data. These however, were disregarded in the current paper.

An example for a resulting Growth Ring Map is displayed in Figure 7. In this particular case, a male wildtype mouse is chosen. Several typical patterns that expressed by the different constellations of Growth Rings can be found in this example:

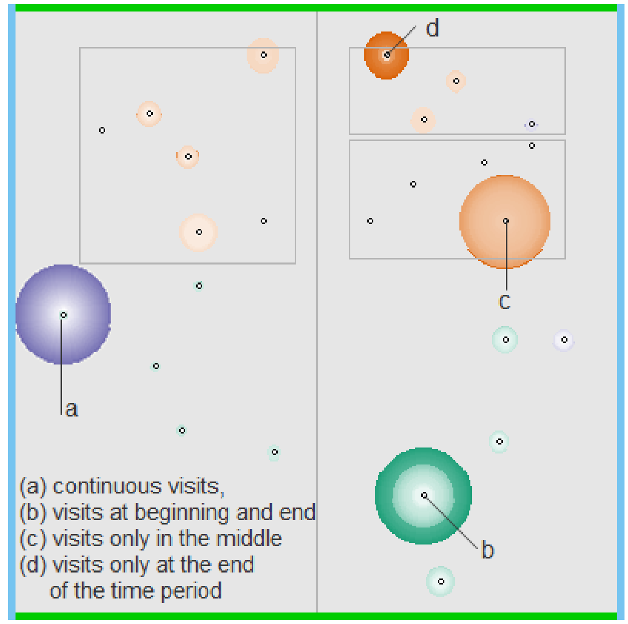


Fig. 7. Example of a Growth Ring Map, showing different constellations of settings that represent different behavioral patterns. The spatial and temporal properties are expressed by color and gradient, and the number of visits by the length of the Growth Ring. The borders of the map indicate gender (male=blue, female=pink) at left and right borders and condition (wildtype=green, transgenic=red) at top and bottom borders.

a. Continuous and high number of visits at a watering place, resulting in many pixels around the sensor and Growth Rings with continuous gradient values.

b. High number of visits at a ground floor sensor in the beginning of the time period (bright colors at the inner Growth Rings) and at the end of the time period (intense color at the outer Growth Rings of the sensor).

c. High number of visits at a higher floor sensor only at the middle of the time period (medium gradient color at all Growth Rings).

d. Medium number of visits at a higher floor sensor predominantly at the end of the time period (intense gradient colors at all Growth Rings).

5.1 Results

The final step in determining behavioral differences as a function of gender and the wildtype/transgenic category is to map each mouse in a separate Growth Ring Map. To have a fair comparison between individual mice, we remove all mice from the analysis for which we had less than 3 months of sensor data. For the remaining 61 mice we plotted the Growth Ring Maps as shown in Figure 9 on which we base all our findings in this subsection.

5.1.1 Territoriality

Territoriality is a typical behavior of male mice and can be clearly seen in the data. The top right area of Figure 9 shows only male wildtype mice. As you can see, these plots usually have a few sensor nodes, which are frequently visited by the respective mouse. Furthermore, most other sensor nodes are almost never visited since they appear as tiny dots on the Growth Ring Maps. Note that our techniques not only enables to display one territory in the lifespan of a mouse, but can also reveal temporal changes in the preferred locations, such as mouse

2376 (J1 in Fig. 9), which in the beginning (light colors) spends most of its time at a sensor close to the top (light orange) and later (dark colors) prefers the sensors in the bottom right (dark green) of the cage.

While territoriality is a predominant pattern for male wildtype mice, the group of male transgenic mice is more homogeneous ranging from a clear breakup of this behavior to normal territoriality patterns.

The opposite behavior to territoriality can be inferred from the Growth Ring Maps of female mice (rows F-J). Most of these mice display movement behavior in all compartments of the cage. However, some sensor nodes appear larger than others as an indication to the preferred habitation of the considered mouse.

5.1.2 Watering places

Watering places (blue) are also equipped sensor nodes, which will be triggered when a mouse comes close, usually for drinking. It is noticeable that watering places appear considerably bigger in the Growth Ring Maps of male mice, since these mice tend to focus on one particular watering place whereas female mice frequently visit several watering places. Note that while territorial behavior and the preferred watering place appear to be closely linked, there are also a number of exceptions, such as mouse 2288 (C2) or mouse 2436 (C6), which tend to drink at distant places.

5.1.3 Temporal behavior of Alzheimer transgenic mice

When trying to distinguish between healthy and transgenic female mice, it is noticeable that overall there is a tendency that the Growth Ring Maps of female wildtype mice use a larger color spectrum than those of transgenic female mice. This kind of behavior hints to changes in the monitored three months activity pattern. Healthy female mice tend to behave similarly with respect to the overall activity at the beginning and the end of the measured time period as shown by the varying intensity of the colors (light to dark). In contrary to this, transgenic female mice tend to move more towards the end of the three months. For male transgenic mice, this pattern is reversed.

5.1.4 Grouping of mice

Overall, we noticed that there are quite a large number of mice which have at least one counterpart in the same mice group behaving in a very similar way as shown by almost identical Growth Ring Maps. We believe that this due to two reasons: a) The duration of the experiment was 8 months whereas most mice only spent a few months in the cage. Therefore, the territory of a male mouse can be inherited to another male mouse. b) While female mice can move more freely in the cage, we explain the effect by the fact that they tend to prefer some locations, which might be linked to an alpha male.

5.2 Cross-Validation

One popular technique that can be used to cross-validate our findings is MDS (Multi Dimensional Scaling) [23, 2]. The aim of this cross-validation is to show that the results created by Growth Ring Maps technique are systematic and reproducible. The method of MDS applied here was based on a Manhattan distance-function on a vector containing the 27 time series with 91 daily measurements for each mouse. Alternatively, we conducted some experiments with the Fast Fourier Transformation to compare the time series signals of the mice with each other. However, the results thereof were not as convincing as applying MDS on the untransformed data. The output of the MDS is a two-dimensional point representation of the individual mice, in which the distances approximately correspond to the high-dimensional distances of the data points. Therefore, with a high probability clusters in high-dimensional space are visible in the two-dimensional MDS plot.

For our concrete dataset this would mean that mice having similarities in their territorial behavior would be positioned closer to each other, whereas mice with distinct behavioral patterns are more likely to be positioned far apart. Therefore, we would expect to find clusters of similarly behaving mice, which have either same gender and/or wildtype/transgenic properties.
Results of the conducted analysis are shown in Figure 8. The colors on the chart show light blue dots for male and pink dots for female

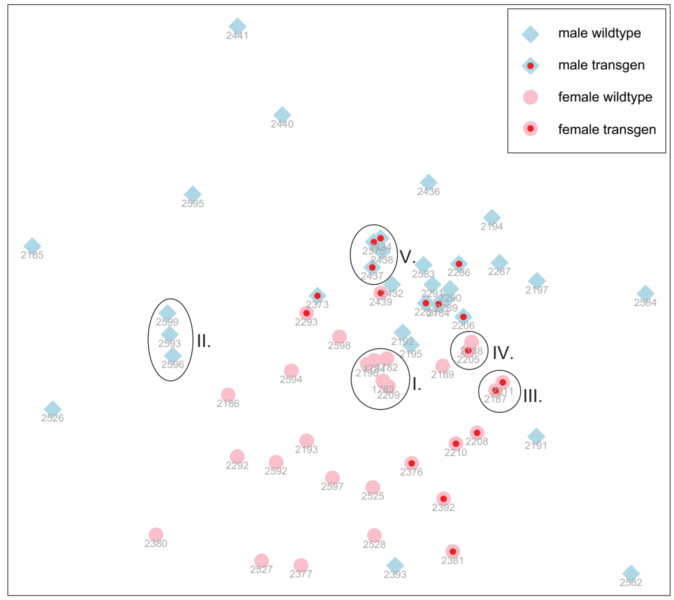


Fig. 8. MDS for clustering mice by their gender and wildtype/transgenic properties. The clusters confirm findings achieved by the Growth Ring Maps in the previous analysis. There is a clear tendency for male and female mice to separate. While female transgenic mice seem to separate from wildtype mice of the same gender, the plot shows that it is harder to distinguish male transgenic mice from their wildtype counterpart.

mice. Red center points indicate Alzheimer-transgenic mice, whereas wildtype mice are not specifically marked. The representation clearly shows a grouping of male and female mice respectively. There is a tendency that female-transgenic mice are located further right of the plot than female-wildtype. However, the difference between wildtype and transgenic mice among males does not allow a clear clustering.

These results fully support the findings described by Growth Ring Maps. As a proof of concept, we demonstrate that the clusters found in the MDS plot are reflected in similar looking Growth Ring Maps. First, there is a cluster of five female wildtype mice marked as (I) in the MDS plot and on the individual Growth Rings Maps in Figure 9. Second, the cluster marked as (II) consists of three male wildtype mice depicting very similar behavior. Third, it is also possible to find similar spatiotemporal behavior in groups of female transgenic mice like in (III). However, cluster (IV) demonstrates that it is not always possible to separate wildtype from transgenic female mice based on the results of the MDS or the Growth Ring Maps. Finally, cluster (V) shows the same effect for a group of 4 male transgenic and a wildtype mice.

Note that overall there are by far more outliers in male wildtype mice than in any other class. Especially the high activity mice with the large Growth Rings can be easily found in the outer regions of the MDS plot. In general, this states that their behavior is unique with respect to space and time, which can be explained by territorial behavior. Nevertheless, MDS aims only at showing clusters given by the properties of the mice, without providing any insight on territoriality and movement patterns, whereas our Growth Ring Maps provide insight into the actual spatiotemporal behavior of the mice.

6 Conclusions

In this paper we presented methods to investigate spatiotemporal datasets. In particular, we used a dataset containing traces of mouse movement in a controlled experiment with wildtype and transgenic mice. First, we demonstrated how the extracted time series of averaged daily movement can be clustered revealing similar properties for a group containing almost all female Alzheimer transgenic mice and a large cluster of only wildtype mice. However, the remaining 6 clusters either contained too little data or a mixtures of the four labeled mice classes. Second, apart from hinting to some territorial behavior of male wildtype mice, the spatial analysis of sensor logs using a grayscale matrix representation revealed little insightful information. Third, the main contribution of this paper is the presented *Growth Ring Maps* for spatiotemporal analysis of sensor logs.

This novel method consists of a two-dimensional sensor map. We then plot a number of non-overlapping pixels, which are colored according to temporal (brightness) and level information (distinct hue), next to the sensor nodes. By plotting data points of early sensor visits first and those of late visits last, similar to a tree trunk so-called Growth Rings emerge in the visualization. Using a gradient color scale for representing the time is beneficial for the task of analyzing behavioral differences of mice, but takes time to read.

In contrast to the first two approaches, the technique allows to get an overall impression of the individual mouse behavior and to derive group-wise particularities, such as a) territorial behavior of male mice, b) differences in the usage of watering places between male and female mice, c) significant differences between the temporal activity patterns of female and male transgenic mice, and d) grouping of individual mice, which predominantly belong to the same mice class. From studying the created set of maps, it becomes evident that Growth Ring Maps are a powerful tool to investigate spatiotemporal behavior. In particular, we believe that our method is much more effective in displaying the movement behavior of mice than a human expert trying to describe animal behavior by manually monitoring the movement of individual animals over a period of several hours, days or even months.

The results found in the mice dataset were then validated using Multi Dimensional Scaling. Thereby, we focused on matching clusters emerging from the 2D MDS representation with the respective Growth Ring Maps. Moreover, unique Growth Ring Maps can be easily found at the borders of the MDS plots, which indicates that the respective mouse's behavior considerably differs from all other mice.

From the application and validation, it is evident that Growth Ring Maps are beneficial for certain types of tasks and data, which in our case were to determine behavioral differences in the movement of mice by gender and the wildtype/Alzheimer-transgenic property. In our analysis scenario, the number of maps equals the number of mice. A larger set of objects investigated may show an overwhelming set of Growth Ring Maps, which could require methods of dimension reduction, filtering or pre-clustering as a preceding step for an analysis process. Although the technical challenges of the technique are rather simple, allowing a quick implementation of the method, further research is needed to improve the scalability of the number of objects investigated, to evaluate the learnability of the representation, and to assess possibilities for interaction techniques especially in dimension reduction.

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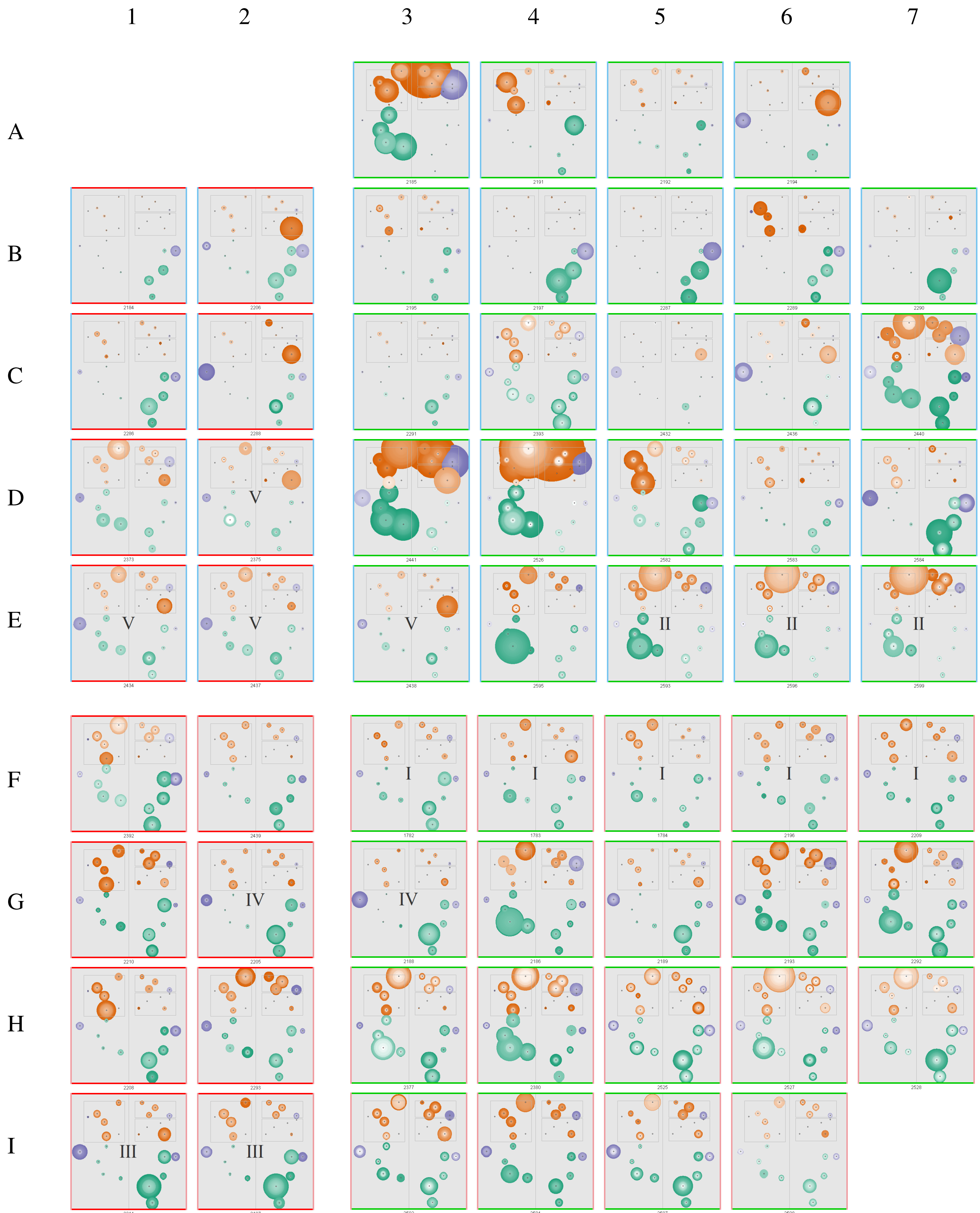

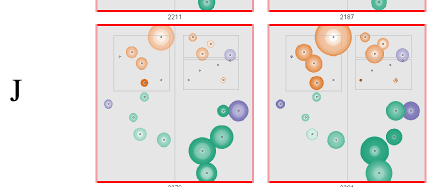

Fig. 9. Results of the Growth Ring Maps technique applied to the mice data set showing territoriality and movement patterns grouped by gender (upper: male, lower: female) and by transgenic (left) vs. healthy (right). Labels in the maps correspond to the clusters from I to V in the MDS validation chart.