Identifying Divergent Building Structures Using Fuzzy Clustering of Isovist Features

Sebastian Feld, Hao Lyu and Andreas Keler

Abstract Nowadays indoor navigation and the understanding of indoor maps and floor plans are becoming increasingly important fields of research and application. This paper introduces clustering of floor plan areas of buildings according to different characteristics. These characteristics consist of computed human perception of space, namely isovist features. Based on the calculated isovist features of floorplans we can show the possible existence of greatly varying alternative routes inside and around buildings. These routes are archetypes, since they are products of archetypal analysis, a fuzzy clustering method that allows the identification of observations with extreme values. Besides archetypal routes in a building we derive floor plan area archetypes. This has the intention of gaining more knowledge on how parts of selected indoor environments are perceived by humans. Finally, our approach helps to find a connection between subjective human perceptions and defined functional spaces in indoor environments.

Keywords Indoor navigation · Floor plans · Archetypal analysis · Isovist features

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1 Introduction

Navigation is one of the most popular use cases for Location-Based Services (LBS) (Gartner et al. 2007; Gartner and Rehrl 2009; Gartner and Ortag 2011; Krisp 2013; Krisp and Meng 2013). In particular, navigation inside buildings, also referred to as indoor navigation, has gained increasing attention in recent years. Estimations of Shekhar et al. (2016) state that people currently spend 10–20 % of their lifetime using LBSs and around 80–90 % of their lifetime in indoor environments. One area of LBS applications is the calculation of routes for visitors of large buildings, e.g., hospitals (Hughes et al. 2015), fairs, or airports (Ruppel et al. 2009). Also, non-human entities like autonomous mobile robots in store houses or non-player characters in computer games utilize such geospatial trajectories (Zheng and Zhou 2011).

Besides finding a shortest path between two given points, the calculation of alternative routes is an important task. There are several definitions for quality metrics for alternative routes in street networks, see for example Camvit (2013), Delling and Wagner (2009) and Kobitzsch et al. (2013). The first definition of alternative routes in indoor navigation scenarios is given by Werner and Feld (2014), where algorithms for creating said routes have been proposed as well. Subsequently, the concept of archetypal routes has been defined in Feld et al. (2015) using archetypal analysis (Cutler and Breiman 1994), a multivariate data analysis and clustering mechanism to find the most extreme observations or pure types inside a given dataset. In that work, the authors have used simple features like the area of the convex hull of a route or the overlength regarding the shortest path.

How humans visually perceive the environment has got a large influence on both navigation performance and emotional response. Franz and Wiener (2008) illustrated that isovists and visibility graph measures are able to capture behaviorally relevant properties of space, allowing the prediction of affective responses and navigation behavior. Emo et al. (2012) found connections between streets' spatial geometry and spatial decisions with space syntax as an interpreter. Unlike outdoor road networks, indoor environments are restricted by walls and other obstacles such as furniture and installations. They also provide navigable space with more degrees of moving freedom.

However, it is still unclear how to incorporate visibility properties of an environment into LBS applications (e.g., navigation systems) to provide users reasonable choices. Different from psychological and behavioral researches, we use perceptual properties in a reversed way. We first inspect perceptual differences among different locations of an environment. Then we use these results to create alternative routes to enable users to have different perceptual experiences when they traverse the environment. Basically, the main idea is to use extreme types of indoor perception to cluster freely walkable space into functional areas. To achieve this goal, we combine the concepts of archetypal analysis (Cutler and Breiman 1994) and isovist features (Benedikt 1979).

Our first contribution creates insights about a building's structure by using just the plain floorplan itself. For this, we calculate isovist features for all accessible points on the map and cluster them via archetypal analysis. The key benefits of using archetypal analysis are the identification of the most extreme observations and the use of multiple features at the same time. This results in the classification of indoor areas and its surroundings into values like entrance areas, corridors, halls or streets.

Our second contribution expands the idea of archetypal routes (Feld et al. 2015) and analyzes the effect of isovist features on the clustering of a set of routes traversing a building. Thus, we identify a small set of proper alternative routes between two points based on perception features only, i.e. isovist measures, and not geometric measures regarding the routes themselves.

2 Background

2.1 Archetypal Analysis

Cutler and Breiman (1994) define archetypal analysis as a statistical data analysis technique. The results of archetypal analysis are defined clusters, which are comparable to the results of other data clustering methods (Kaufman and Rousseeuw 1990; Jain and Dubes 1988) as, for instance, k-means clustering (Hartigan 1975). In contrast to the last mentioned examples of hard clustering, archetypal analysis is a fuzzy clustering technique.

The general goal of clustering is to organize data in feature space into useful partitions. This organization of a collection of patterns into clusters is often based on similarity (Jain et al. 1999). Archetypal analysis partitions certain amounts of not necessarily equally spaced data. In contrast to traditional clustering techniques, archetypal analysis searches for the points on the outer rim of data space. It approximates the convex hull of the data mainly by looking for data points that are maximally distinct from each other. This characteristic renders archetypal analysis fundamentally different to other clustering techniques, as the aim is to find "pure types" within specific data sets (Eugster and Leisch 2009).

The original algorithm is described in Cutler and Breiman (1994). Seiler and Wohlrabe (2012) propose an iterative version of archetypal analysis which alternates between two steps. The idea is to find a convex hull approximation (in data space) using relatively few points, which results in solving a linear optimization problem.

Referring to the practical approach in this work, we consider a data set with N observations, which in our case are routes consisting of pixel values, and m attributes. This results in a $N \times m$ matrix X. Afterwards, the number k of archetypes to be extracted needs to be defined. These archetypes are then specified by the $k \times m$-

dimensional matrix Z, which is computed by minimizing the residual sum of squares (RSS):

$$RSS = \left\| X - \alpha Z^T \right\|_2$$

Consequently, we compare matrix X with the product of the $N \times k$-dimensional coefficient α and the matrix of archetypes Z. In the formula of the RSS the part $\| \cdot \|_2$ represents a fitting matrix norm, which in our case is the L_2-norm. Subsequently, α is the coefficient matrix, which is needed to generate X from a given set of archetypes Z. Further mathematical and computational details of the algorithm are explained in Eugster and Leisch (2009). Archetypal analysis by Cutler and Breiman (1994) is also called alternating least square algorithm since it alternates between calculating the best coefficient α for given archetypes Z and calculating the best archetypes Z for given coefficient α. Archetypal analysis iterates until it finds a minimum. It always terminates, but does not necessarily find the global minimum of the RSS. It can find a local minimum instead of, for example, the best approximation of the convex hull of the data using k points.

There is no universal rule for determining the initial number of archetypes k. The common approach for its determination is the so called “elbow criterion”: a flattening of the RSS scree plot is indicating a potentially good value of k.

Our literature review on archetypal analysis includes publications that focus on details like numerical issues, stability, computational complexity and robustness. These issues are based on concrete applications and mentioned in Cutler and Breiman (1994), Eugster and Leisch (2009, 2011) and Seiler and Wohlrabe (2012). Recently, applying archetypal analysis is becoming popular in economics (Eugster and Leisch 2009). Relatively unexplored is the use of archetypal analysis with geodata.

2.2 Qualitative Perceptual Analysis of Space

Human beings experience surrounding environments through senses including seeing, hearing, and smelling. The objects that are seen usually shape the most basic and important part of our experiences. Much effort has been made by behavioral researchers and environmental psychologists to explore how visual properties of an environment affect human’s subjective feelings and behaviors in it.

The term *isovist* has been introduced by Tandy (1967) as a visible space obtained at a specific place. Benedikt (1979) then provided a formal definition of isovists with a set of analytic measurements to enable quantitative descriptions of spatial environments. Isovist fields characterize the whole environment with recorded measurements. Using a discretized representation—either some selected locations or evenly distributed locations—is practical to approximate isovist fields (see e.g. Peponis et al. 1997; Batty 2001). To the best of our knowledge, the selection of representative locations and granularity of the discrete representation still have no universal answers. There is always a compromise between coverage (Davis and Benedikt 1979) and computing costs. In most of the mentioned researches, isovist analysis is performed on 2D representations, such as maps and floor plans. Though Emo (2015) advocates isovist analysis in 3D space, she admits such egocentric isovist analysis is still far from mature.

Space syntax (Hillier and Hanson 1984) and visibility graph (Turner et al. 2001) are also frequently used tools that focus on visual perception. Space syntax captures mainly topologic structures (or inter-visibility connections) of an environment, and defines no explicit geometric measurements in Euclidean space, which isovists are capable of, while visibility graph counts the inter-visibility between locations.

In the context of walkable area and alternative routes, we assume that any accessible location can potentially be traversed. We focus on properties of each single location in an environment. Since the generation of visibility graph shares the same idea as generating isovist fields, measurements on visibility graph can easily be integrated in future studies.

3 State of the Art

Orientation in indoor scenarios is still a problem to solve, since street names or other characteristic landmarks are missing, unlike in outdoor environments (Yang and Worboys 2011; Viaene et al. 2014; Ohm et al. 2015). Since the focus of this work is on indoor environments we want to review research on indoor wayfinding, perceptual analysis and the representation of indoor space.

3.1 Indoor Wayfinding and Navigation in Complex Buildings

Early research on indoor navigation has been initiated by Best (1970) where challenges of wayfinding in complex indoor environments have been formulated. The work of Best (1970) deems reasoning on choice points, distances and changes in direction to be relevant for wayfinding in road networks or buildings (Hölschner et al. 2005).

Hölscher et al. (2005) stated that the difficulties of wayfinding in complex buildings are connected with individual spatio-cognitive abilities and the architecture of the building. Therefore it is obvious to link research on architectural design and human spatial cognition to gain knowledge in the field of indoor wayfinding.

Wayfinding behavior in complex buildings has already been investigated by studies coming from the community of environmental psychology (Hölschner et al.

2005). Typical buildings are hospitals (Haq and Zimring 2003), shopping malls (Dogu and Erkip 2000) and airports (Raubal 2002). In general, spatial knowledge and wayfinding acquisition are complex tasks (Li et al. 2011).

3.2 Perceptual Analysis and Wayfinding Behavior

Isovist features and axial lines have shown high predictive power in previous research. Wiener and Franz (2004) studied the interrelations between isovist measures and performance on navigation related tasks. They derived isovist measures from visibility graphs (Turner et al. 2001). Their experiment illustrated the meaningfulness of isovist measures, however, the most important wayfinding behavior—orientation—was not considered. Davies et al. (2006) proposed to use isovist features and build prediction models for spatial orientation and implied that correlations among isovist measures have important implications. By respecting the spatial configuration in indoor environments, we can derive measures for describing the imagined spatial perception of moving persons. Important for these cases are fields of vision (Schwab 2016), which are isovists that are connected with individual vantage points (Turner et al. 2001). This is strongly connected with the previously mentioned wayfinding strategies, mainly due to the fact that isovist measures are information sources for individual decision making. The base for these findings comes from previous studies by Conroy (2001), Wiener et al. (2011) and Schneider and König (2012), who evaluated the potential of isovist measures by providing different case studies in indoor environments.

3.3 Representation of Navigable Space

Shekhar et al. (2016) state that a major research question on indoor localization includes the conversion of indoor floor plans (e.g. CAD drawings) into navigable maps. Lorenz et al. (2013) argue that the map design of indoor floor plans is more complicated to realize than outdoor environments since people usually walk across different elevation levels of buildings. This could be solved by including 3D indoor space visualization (Brown et al. 2013) or by a combination of 2D floor plans for different elevation levels. Cartographic considerations on floor plans show that most examples are inappropriate as they are non-generalized and too detailed for simple orientation (Lorenz et al. 2013).

In general, there are still just few publications on cartographic design guidelines for indoor maps (Lorenz et al. 2013). Nevertheless, Puikkonen et al. (2009), May et al. (2003) and Vinson (1999) deliver some results from provided user studies on created indoor environment maps.

Other questions connected with floorplans and navigable maps consist of estimating reliabilities of indoor positioning and the handling of missing indoor building information (Shekhar et al. 2016).

Richter et al. (2009) solve the question of how to represent indoor space by introducing a hierarchical representation of indoor spaces. In general we can state that it is possible to describe indoor environments similar to outdoor environments as an arrangement of elements in space, which is also referred to as spatial configuration (Schwab 2016). This spatial configuration consists of topologic space information together with indoor geometry and the arrangement of objects (Frankenstein et al. 2010), which is the key information for indoor navigation in many approaches (Brown et al. 2013).

4 Methodology

Our concept combines two different approaches for classifying indoor environments, namely isovist analysis and archetypal analysis. The former focuses on estimated human senses for optical perception of inner building structures. The latter makes use of given features, in our case isovist measures, and derives extrema of their appearance, namely archetypes. Like Krisp et al. (2010, 2012a, b) we have used the main building of the Technische Universität München (TUM) in Munich for our case study, which is characterized by its complexity and the high number of entrances. The two mentioned aspects are mainly caused by the possibility to enter varying elevation levels differently and by the diversity of options to traverse the building by using more than twenty entrance points. There is a high number of alternative routes to be expected, which will be one of the leading aspects for our case study. The difference between our idea and previous visibility analysis approaches that use isovist measures in indoor environments is the way of inspecting the calculated isovist measures: all measures are utilized simultaneously for calculating the archetypes. The aim of this approach is to design a functional segmentation method for indoor spaces. This includes the classification of indoor areas and its surroundings into values like entrance areas, corridors, halls or streets.

The actual investigation of the maps and routes represented in a multidimensional feature space will be realized using an extension of the archetypal analysis framework proposed by Feld et al. (2015). See Fig. 1 for an overview of the algorithm's workflow.

4.1 Input Requirements

As mentioned in the previous section, we adopt a 2D representation to depict the study environment. The representation can be generated from floor plans or street maps or the mix of both. 2D polygons represent walkable areas, their boundaries

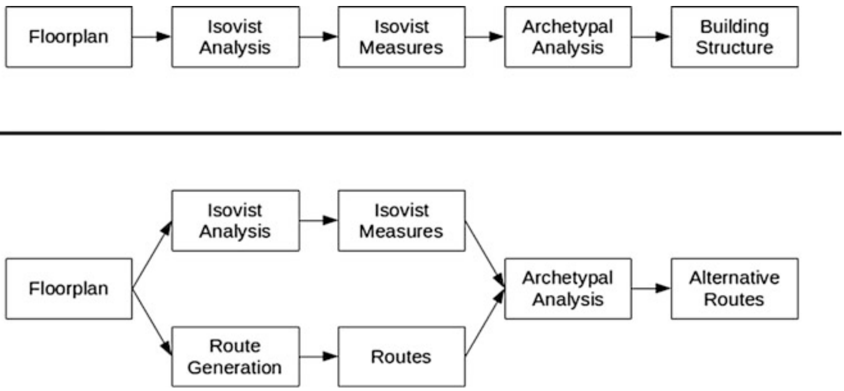

Fig. 1 Workflow for analyzing a given floorplan (*top*) and a set of routes (*bottom*)

and inner holes represent restrictions such as walls, installations, and other obstacles. This representation is also reasonable for multi-level indoor environments. Each level of a building is represented in 2D separately. It does no harm to isovist analysis when the calculation is based on a single level since ceiling and floor are nontransparent. To calculate isovist fields for the full description of the environment, we use regular grid tessellation and select the geometric center of each cell as the representative location. The appropriate grid resolution should be determined to capture meaningful properties of the environment and fit the application scenario. A too coarse resolution may fail to reveal changes of isovist features in transitional areas like doorways or turnings. A 0.5 m resolution is enough for our case study. A finer resolution will reveal more details, however leads to more computing costs (time and storage). Besides, 0.5 m is also a reasonable approximation of body-size and normal walking step length for human navigation and wayfinding scenarios.

A set of routes between a given start and goal will be created using the penalty algorithm as proposed in Werner and Feld (2014). The algorithm works on plain bitmaps and creates a node for each white pixel and an edge for all neighboring white pixels. The edge weight is set to 1 for horizontal or vertical edges and accordingly to $\sqrt{2}$ for diagonal edges. The algorithm iterates between performing shortest path routing using Dijkstra's algorithm (Dijkstra 1959) and increasing the edge weights of the shortest path just found. Thus, by iteratively increasing the edge weights the resulting shortest path will change with time.

4.2 Feature Extraction

In this paper we extract isovist features by following Benedikt's definition and measurements (Benedikt 1979). A single isovist is the set of all points in space that

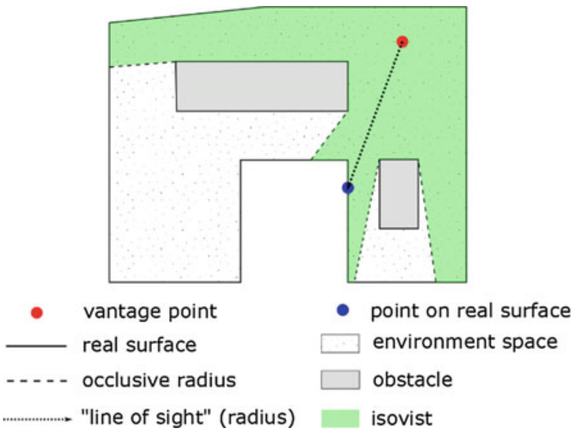

Fig. 2 Definition of an isovist by line-of-sight and its corresponding features

are visible from a given point (vantage point) in the space. Figure 2 illustrates an exemplary isovist with occlusive radius and line-of-sight.

The six measurements are:

(a) A_x, the area of the isovist;
(b) P_x, the real-surface perimeter of the isovist that indicates the amount of obstacle surface visible from a vantage point;
(c) Q_x, the occlusivity of the isovist measures the length of the occluding radial boundary;
(d) $M_{2,x}$, the variance of the radius measures the distribution of the radials length;
(e) $M_{3,x}$, the skewness of the radius measures the asymmetry of the distribution of the radius length;
(f) N_x, the circularity of the isovist which can be calculated by the following formula,

$$N_x = |\partial V_x|^2 / 4\pi A_x$$

where $|\partial V_x|$ is the perimeter of the isovist.

We calculate the six isovist measurements using the given floorplan in vector format and rasterize the calculated values afterwards for further processing.

4.3 *Clustering Building Structures and Routes*

As stated in the paper's introduction, we focus on the extraction of insights about a building's structure as well as on the identification of a small set of proper alternative routes between two given points. For doing so, we need to transform the given map, isovist features, and routes into a form that can be processed by archetypal analysis.

When analyzing the building structure we consider each pixel of the floorplan as an observation. Thus, we have $N = r \times c$ observations, whereas r is the number of pixel rows and c is the number of pixel columns. Each observation has got $m = 6$ attributes $\{A_x, P_x, Q_x, M_{2.x}, M_{3.x}, N_x\}$. Thus, the input of the archetypal analysis is the $N \times m$ matrix X consisting of all the floorplan's pixels each having six features.

The clustering of a (huge) set of routes each having the same start and goal behaves slightly different. Each route consists of multiple pixel coordinates indicating the trajectory's course. We define each route to be an observation and for each route pixel we determine the corresponding isovist measures from the previously calculated matrix. For each route and for each of the six isovist measures we calculate the minimum, maximum, mean, median and variance. Thus, the input of the archetypal analysis is the $N \times m$ matrix X consisting of all the given routes each having $5 \times 6 = 30$ attributes.

5 Results and Discussion

We focus our discussion on a real world scenario, namely the main building of the Technische Universität München (TUM) and its surrounding area (Theresienstraße, Arcisstraße, Gabelsbergerstraße, Luisenstraße). We have simplified the original floorplan (e.g. removal of doors) in order to be compatible with the route generation algorithm in use.

5.1 Clustering the Map

Our first contribution is about identifying functional space inside a given, unlabeled floorplan. Thus, we perform archetypal analysis on the floorplan's isovist measures. We utilized each walkable pixel as an observation and calculated the corresponding six isovist measures as the attributes.

Archetypal analysis works by approximating the convex hull of the observations in the multidimensional feature space. A common way to estimate a suitable value for the number of archetypes k is to inspect the resulting approximation errors, i.e. the residual sum of squares (*RSS*). A flattening of the curve indicates that a further addition of an archetype would not help to improve the accuracy of the approximation. For our evaluation we have performed archetypal analysis with numbers of archetypes ranging from $k = 1$ to $k = 10$ and repeated the calculations multiple times to prevent local minima. The scree plot of the resulting *RSS* as shown in Fig. 3 suggests to choose a value of $k = 4$, $k = 5$, or even $k = 7$. From an application point of view a high number of archetypes like $k = 7$ harbors the danger that the

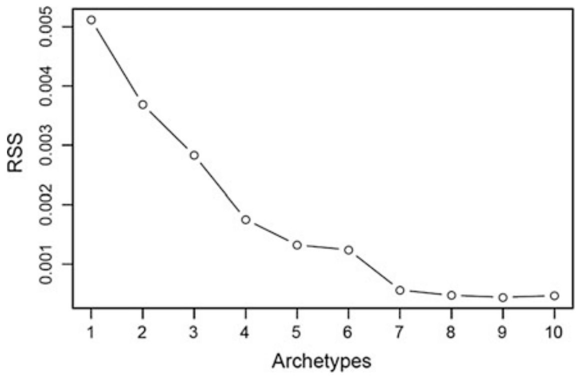

Fig. 3 Scree plot showing the value of k and the resulting residual sum of squares (RSS)

interpretation gets confusing. Thus, for the further course of this section we will focus on up to five archetypes.

Archetypal analysis is a so-called fuzzy clustering method meaning that each observation is represented by a convex combination of the identified clusters, i.e., the archetypes. We now discuss the points in the map that have a certain level of assignment to an archetype. Graphically spoken, we highlight and discuss the observations (pixels) that are some kind of "near" to an archetype in the feature space. Thus, we assign a pixel to an archetype if the corresponding value in the coefficient matrix α is higher than a defined threshold. Of course, the threshold for the definition of an "archetypal pixel" can be varied, but for the sake of clarity and visualization we restrict ourselves to the representative threshold of $\alpha > 0.5$.

The case $k = 2$ is often hard to interpret: If the analyzed data set contains several natural clusters, it happens that they get uncontrollably combined. The left-hand side of Fig. 4 shows the parallel coordinates plot for $k = 2$. The abscissa shows the six isovist features, the gray lines represent all observations (i.e. all walkable pixels) and the colored lines the identified archetypes. Basically, the red archetype can be summarized as having high isovist measures while the green archetype has got low values. Just the skewness of the radials $M_{3.x}$ seems quite similar. Roughly speaking, high isovist measures indicate that the point of view is a good lookout (large isovist area A_x) and that in turn involves much obstacle surface to be seen (high real surface P_x). In the case at hand, the green archetype has got very low values. In particular the low radial's variance $M_{2.x}$ indicates that the area of view (the isovist itself) has got a more regular shape. The right-hand side of Fig. 4 shows the corresponding coloring of pixels; it accompanies with our preliminary interpretation. Basically, the red pixels represent places in the floorplan where large parts of the space can be seen. Green pixels are the opposite of that, since the view is strongly restricted.

The left-hand side of Fig. 5 focusses on $k = 3$. It shows that the green archetype stayed nearly the same. In fact, all the values are lower than when using $k = 2$. The red archetype, however, still has got high levels of values, but they are somehow more "radical". The isovist's area A_x is extremely high and the moderate real-surface P_x, the high occlusivity Q_x, and the high variance $M_{2.x}$ indicate a more "diversified" line-of-sight. Again, this archetype will be something like open space.

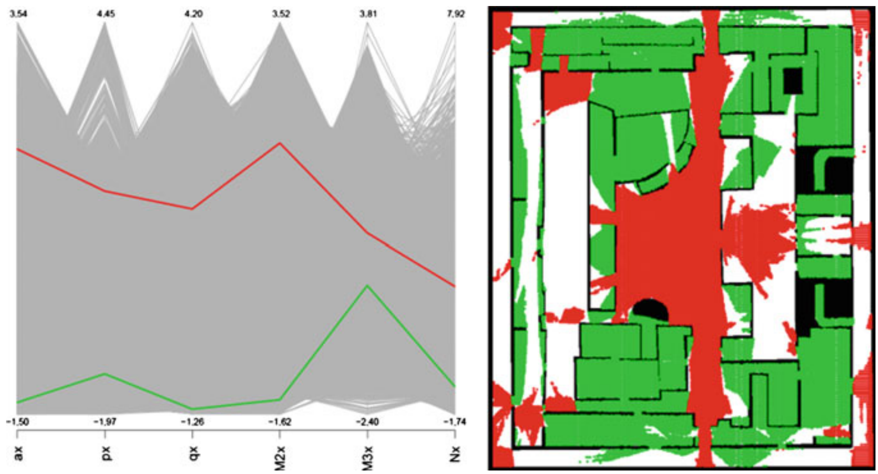

Fig. 4 Parallel coordinates plot for $k = 2$ (*left*) and correspondingly colored pixels with a threshold of $\alpha > 0.5$ (*right*)

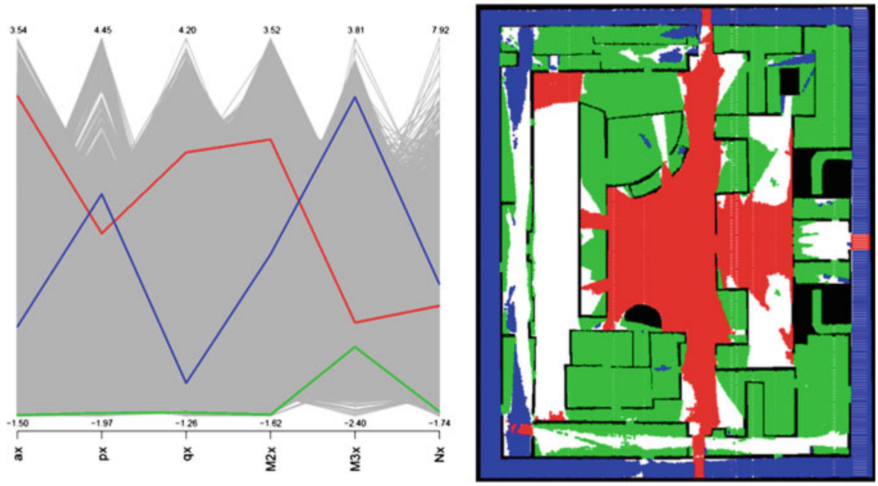

Fig. 5 Parallel coordinates plot for $k = 3$ (*left*) and correspondingly colored pixels with a threshold of $\boldsymbol{\alpha} > 0.5$ (*right*)

The new blue archetype is interesting, since the moderate area of visibility A_x, plenty of walls to be seen (high P_x) and the low values of occlusivity Q_x suggest a very uniform and simplistic structure. If we follow the initial interpretation by looking at the right-hand side of Fig. 5, we see red pixels representing free and open space, but with one obvious difference to the results of $k = 2$: the structure of the red area is more compact and just pixels having a “large outlook” are selected.

The green archetype can again be interpreted as areas where the view is restricted, such as rooms or smaller halls. The new blue archetype can be interpreted as points in the map where the field of vision is very restricted in two directions and very wide in the other two directions, like in narrow hallways—or as in our case—the streets around the building.

Please note the white pixels of the floorplan indicating that the corresponding α values are all below the threshold. This means that the observations are somehow poor to be described using the identified archetypes. When looking at the white area at the left-hand side of the floor plan in Fig. 5 it is noticeable that there are properties from each archetype: Somehow the area is room-like due to the regular shape and the restricted view, somehow it is open space due to its large area and somehow it is like a hall or a street due to the length.

Figure 6 shows the top pixels for $k = 4$ (left) and $k = 5$ (right), the number of archetypes that are most suitable at least when inspecting the scree plot in Fig. 3. The corresponding parallel coordinate plots (not shown) and a visual inspection of the pixels indicate that the green archetype ("rooms") and blue archetype ("halls or streets") stayed nearly the same, just the interpretation of "open space" is split. We still have the red archetype indicating places with a large view, but additionally there is the turquoise archetype that has got deep views into entrances (very high occlusivity Q_x, i.e. the length of the occluding radial boundary). The right-hand side of Fig. 6 refines that setup further with the pink archetype where a spectator would see much area while having a wall behind his or her back.

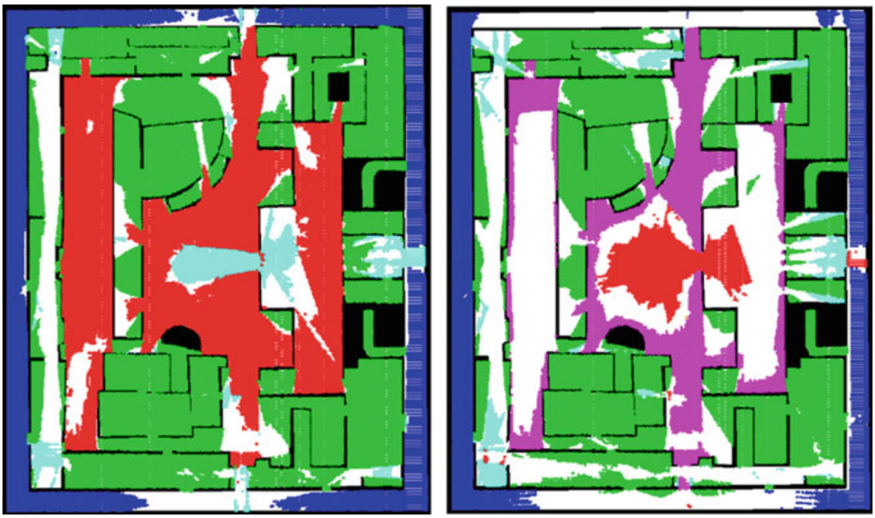

Fig. 6 Colored pixels for $k = 4$ (*left*) and $k = 5$ (*right*) for a threshold of $\alpha > 0.5$

5.2 Identifying Alternative Routes

Our second contribution is about analyzing the effect of isovist features on the clustering of a set of routes between two given points in order to generate a small set of alternative routes. To this end, we created sets of routes between multiple pairs of starts and goals inside floorplans. In the work at hand we used a representative result for a set of 400 routes going from the main entrance of the building to another entrance at the opposite side of the building. We used the penalty algorithm as proposed in Werner and Feld (2014) to create the routes.

Figure 7 shows a plot of the resulting routes that traverse the map in multiple ways ranging from completely detouring the building, going with variations through several rooms, transiting the patio, etc. Through visual analysis of the routes created, one can identify a strong correlation with real movement flows of students during semesters on working days. Like stated before, our second contribution is about extracting different archetypes of alternative routes, thus we try to reduce the size of the set of routes from 400 to a low single-digit number. In terms of archetypal analysis we consider each route as an observation. For each route, we calculate the minimum, maximum, mean, median, and variance of the isovist measures. Thus, for each of the 400 routes we have got $5 \times 6 = 30$ attributes.

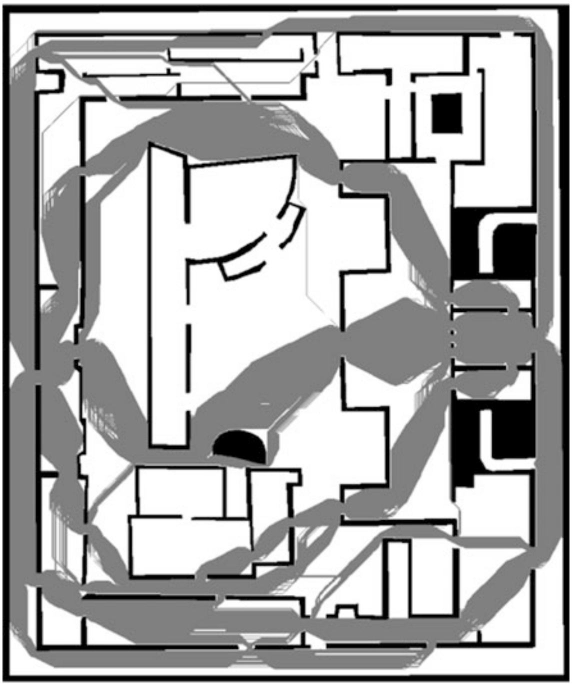

Fig. 7 Set of routes used for the discussion

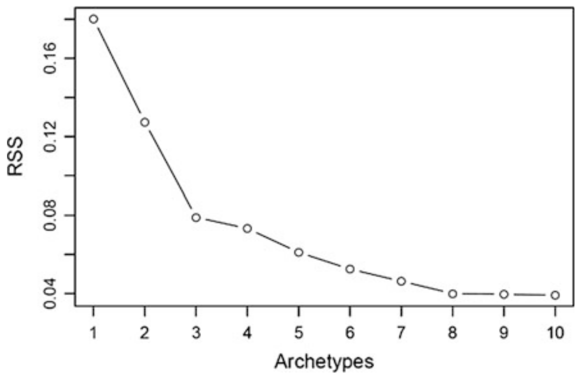

Fig. 8 Scree plot showing the value of k and the resulting *RSS*

As in the previous section we consult the scree plot of the *RSS* to check for an indication of a proper value of k (see Fig. 8). There is a strong bend of the decrease at $k = 3$ visible, what also holds as an appropriate value from an application point of view.

The calculated archetypes, i.e., the configurations of features, do not necessarily exist or can be observed. Thus, and according to Feld et al. (2015), we call the archetypes' nearest neighbor in the feature space the "realized archetypal route". Figure 9 shows the corresponding archetypal routes for $2 \geq k \geq 5$.

The top-left part of Fig. 9 shows the case for $k = 2$. The red route traverses the map through the center while having a large view in the patio and proceeds quite twisting and winding to the goal. The green archetype is, at least to this end, the complete opposite. It is a straight path with regular turns and a more restricted view. It follows the street around the building and traverses some rooms in the northern and western part of the building.

The result for $k = 3$ is shown in the top-right part of Fig. 9. The red archetype is again a windy route going through the open space. The green archetype has changed a bit, since it is more "extreme" in being very straight with a minimum number of turns. The new blue archetype is quite complicated; it traverses the map in a diverse way and has got narrow parts that go through different rooms, doors, and hallways.

When calculating $k = 4$ archetypes (bottom-left part of Fig. 9) we basically get the same three routes as before, although archetypal analysis is not nested per se. Additionally, there is the turquoise archetype being a kind of mix between the green and blue archetype. This route is quite straight with few turns, but mostly uses rooms and doors instead of the more extreme, i.e., even straighter, green route which uses the road.

The bottom-right part of Fig. 9 shows the results for $k = 5$. The routes are identical to the ones before, but additionally, the new pink route is—at least at a first sight—very similar to the red one. It also traverses the patio but runs around the isolated building to the top.

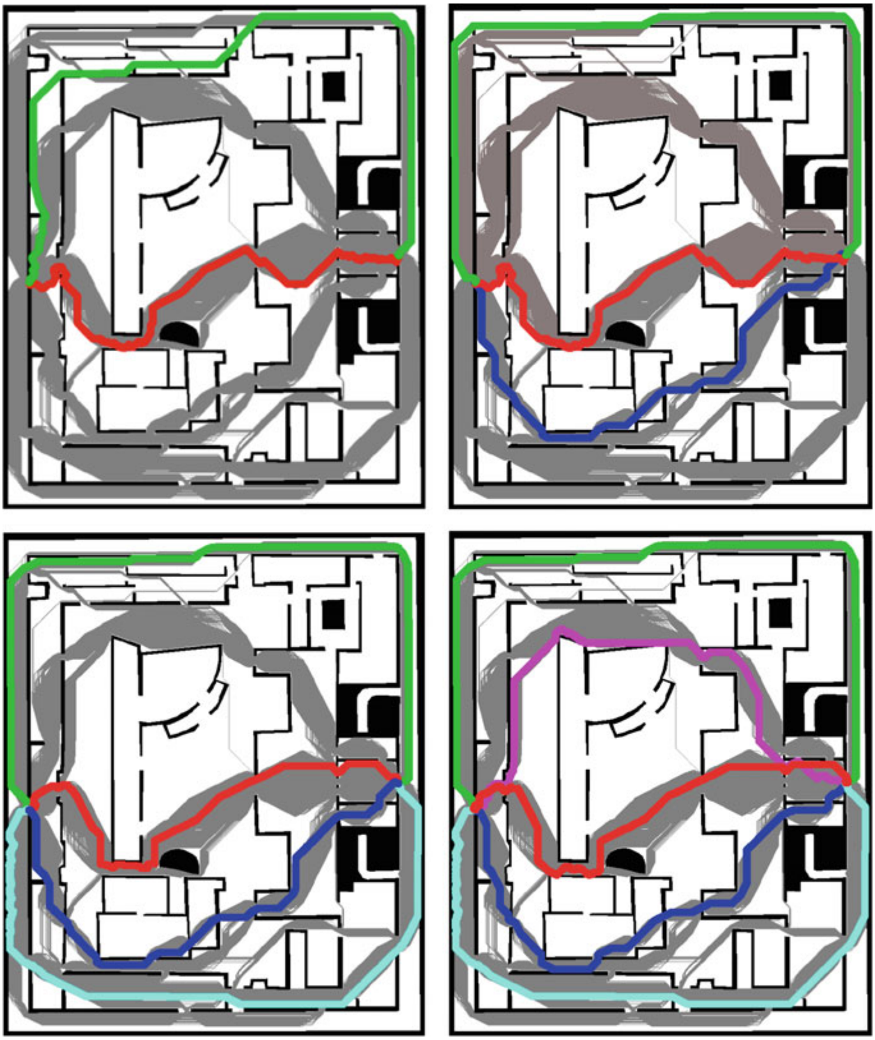

Fig. 9 Archetypal routes for $k = 2$ (*top left*), $k = 3$ (*top right*), $k = 4$ (*bottom left*), and $k = 5$ (*bottom right*)

All five routes are proper alternatives with very different characteristics. Beginning from $k = 6$ the resulting routes start to "collapse". That means that at least two archetypal routes lie over another (note: in the observation space, not in the feature space).

5.3 Sets of Archetypal Routes

Just focusing on a single representation of an archetype can sometimes bias the interpretation. Just like with the clustering of the map, we now focus not only on the nearest neighbor of each archetype, but on the observations that reach a certain threshold regarding the coefficient matrix α.

Figure 10 shows this for $k = 3$ and a threshold of $\alpha > 0.8$. It can be clearly seen that the identified archetypes are based on the impression while traversing the building and not on their geographic location. The green archetype consistently traverses the patio having several variations at the start and the end of the route. The blue archetype characterized by going very straight through the streets or long and narrow halls can be found not only at the top of the floorplan, but also in variations at the bottom of the map. The variations, be it shortcuts or detours, are located in rather narrow spaces. Finally, also the red archetype is variable and consistently follows variations of rooms and doors, but all the time in a quite complicated fashion.

Summarized, the resulting sets of routes are useful in application scenarios where variety is desirable. Think of computer games where non-player characters choose a set of archetypal routes based on their strategy and out of this set a random concrete route to surprise the player. Another use case is a navigation system for pedestrians that proactively prevents bottlenecks via non-deterministic route suggestions.

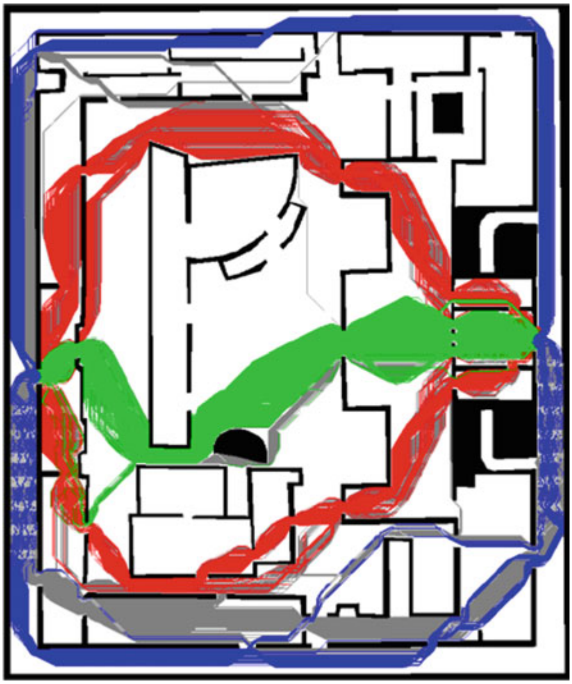

Fig. 10 *Top* routes for k = 3, i.e. routes with a corresponding coefficient value of $\boldsymbol{\alpha} > 0.8$

5.4 Archetypal Routes: Features Versus Time

To further interpret the properties of archetypal routes, we need to take a closer look at the isovists of each of the selected locations along the route. To keep the explanation clear and simple we have chosen the archetypal routes for $k = 2$ as an example. We also adopt a visual analytics way rather than using statistical analysis as in many isovist related works already done.

Figure 11 depicts the case of archetypal routes for $k = 2$. The top row corresponds to the red route and the bottom row to the green route in Fig. 9, top-left. The six measurements are normalized and plotted in a stacked area chart (left-hand side). Isovists for each location are centered to have the same vantage point in order to form a radar-like view (right-hand side). This visualization is related to the Minkowski Model (Benedikt 1979), however, the original model is difficult to perceive clearly when hundreds of isovists are stacked along a route. Our visualization loses time dimension information, but it is sufficient to capture the pattern changes of isovists along different routes. In this example, we can already find obvious differences between the two archetypal routes indicating that our method does not only find routes that are geometrically different, but also with different perceptual properties. There are still details to be extracted from this visualization in future work.

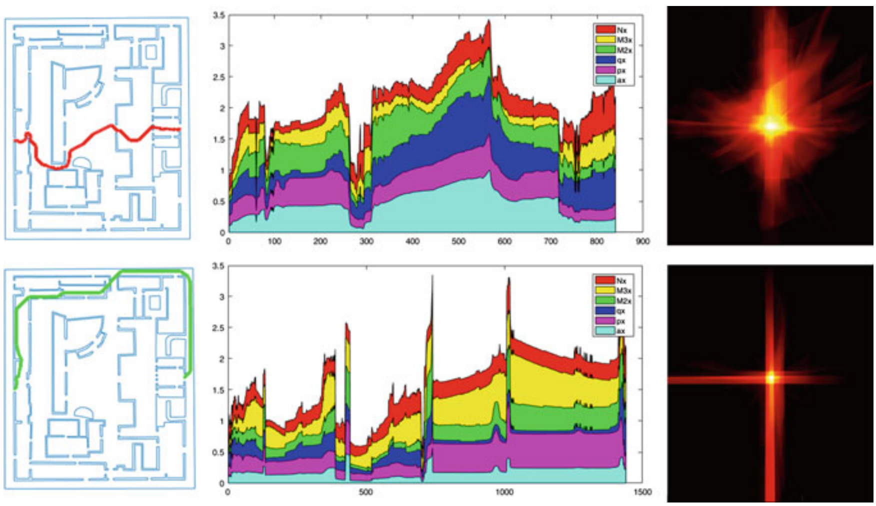

Fig. 11 Archetypal routes for $k = 2$ with area plot for the normalized isovist features (*mid*) and radar visualization of stacked isovists along a route (*right*). The top row corresponds to the red route (*top left*) and the bottom row to the green route (*bottom right*) in *Fig.* 9 top left

6 Conclusion

This paper proposed to use archetypal analysis, a fuzzy clustering method, to gain insights of an environment based on modelled perceptual properties (visibility). Our approach is able to find archetypes, i.e., extreme types, of perceptual properties of the given environment. By applying this information we can create proper alternative routes going through a building that enable different user experiences when traversing the environment. Previous psychological and behavioral research tried to establish correlations between perceptual properties and wayfinding behavior. Our method enables the creation of routes with extremely different visibility properties. Additionally, we segment 2D Euclidean space into areas with fundamental differences depending on their visibility (based on the isovist feature values).

In future work we want to investigate other isovist measurements for extracting environment information and for creating alternative routes. Also we try to focus on the measurements along the routes using the stacked isovist visualization and visual analytics. Finally, different route generation algorithms together with routes having different start and goals need to be examined.

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