Analyzing architectural space: identifying salient regions by computing 3D isovists

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ABSTRACT: Spatio-cognitive properties – including the capacity to evoke a sense of place or support wayfinding – are amongst the most important considerations in the design of large urban and architectural spaces. Both wayfinding and spatial identity rely on the capacity of a space to be noticeably distinct; a property that is called saliency. However, there are relatively few experimental techniques to identify locations that are rich in such visual properties and those that do exist were typically developed in the 1980s using only two-dimensional viewshed geometry. In contrast, this paper describes the use of 3D isovists to develop a salient region estimation technique for architectural and urban environments. The underlying method of saliency estimation is based on principal component analysis that is used to compare geometric properties of the areas surrounding a vantage point. Statistical summaries of the 3D isovists are compared in the principal component space to differentiate the monotonous regions from the ones that are more visually distinct. The experimental results reported in this paper are developed using a model of the Villa Savoye to demonstrate that 3D isovists can be used to determine the extent to which an environment supports a capacity for wayfinding. The paper makes two major contributions to architectural computational analysis; first, it demonstrates a consistent, stable 3D isovist method and second, it proposes a quantitative technique for detecting regions with strong visual characteristics.

Conference theme: Design education and computing
Keywords: 3D Isovists, wayfinding, visual properties, structural saliency.

1. INTRODUCTION

One of the questions that spatial psychologists and architectural designers repeatedly ask is, “why do people get lost in buildings” (Carlson *et al.* 2010; 284)? While many factors influence the answer to this question, it has been demonstrated that the quantity and quality of visual informative that is available to a person, from a given location in space, is critical to the generation of coherent mental maps (Golledge 1999; Conroy-Dalton 2005). Buildings and cities that possess relatively uniform or undifferentiated spatial properties are typically regarded as being both lacking in identity and being difficult to navigate around (Lynch 1960; Ellard 2009). Significantly, Carlson (*et al.* 2010) describes such spaces as promoting loss of orientation because they lack “salient landmarks” (287). However, locations with differing levels of spatial information, and especially those that possess a high level of contrasting geometric information have a propensity to be remembered as critical orientation sites (Conroy-Dalton 2001; Haq and Girotto 2003). Siegal and White (1975) describe such sites as possessing “a unique configuration of perceptual events” (23). Montello (1998) agrees, but elaborates that such sites “serve important roles in the organization of spatial knowledge” (144), even though, they “do not in themselves contain spatial information” (144) that is useful; it is only through comparison with other information in the system that they became significant. Viewed in this way, questions about wayfinding and spatial identity in architecture could be regarded as relating directly to the presence, or absence, of salient features.

Since the 1970s, architects, planners and urban designers have attempted to develop methods for the analysis of the visual properties of space that relate to mental maps and wayfinding (Meilinger *et al.* 2009). Many of these have relied on studies of human experience to produce results (Baskaya *et al.* 2004, Werner 2004, Wiener and Franz 2005, Wiener *et al.* 2007). Interest in the geometric properties of vision, often formalized into a study of isovists properties (Benedikt 1979; Turner *et al.* 2001) also posed great potential for this field of research, but have not since been developed specifically to study issues of visual saliency. This is not surprising given that the accurate modeling and estimation of the degree of geometric visual character – what might be called structural salience – is a challenging task. Several factors including isovist visibility, geometric shape, extent of visual area and the shape enclosed around the vantage point all need to be evaluated. Furthermore, accounting for these factors and comparing them over many hundreds of vantage locations can prove to be physically impossible and computationally intensive. This paper approaches this complex issue by demonstrating a repeatable method for evaluating the wayfind-abilty of complex architectural and urban environments. Specifically, the paper proposes a computational methodology for determining structural salience employing 3D isovists. The application of 3D isovists is intended to imitate, as closely as possible, the human perception capacity. This property, in comparison to alternative social sciences approaches, has a potential universal application. It also ensures that the resolution of saliency is reliant on what is directly visible, rather than what could be inferred indirectly. It derives its theory and application from architectural science and computing and it depends on concepts derived from the field of computer science to evaluate overall features responsible for structural saliency.

The paper demonstrates the application of this method for saliency determination using, as an example, the archetypal modernist house, the *Villa Savoye* at Poissy (near Paris, France) by Le Corbusier. This project, while outwardly minimal and repetitive, has a seemingly complex internal navigation system involving parallel vertical circulation routes, although the presence of particular formal features (including curved partition walls, ramps and a spiral stair) allegedly provide critical orientation points so that a visitor remains constantly aware of their location in the house (Rowe 1976; Ching 2007). Unwin (2010) even argues that it is a building designed explicitly to be discovered through vertical movement, with the difference between each level, in an otherwise regular plan, being signalled by various combinations of courtyard walls and window geometry. Thus, while this building was chosen to demonstrate a method of saliency determination, this is also a structure where some intuitively determined suggestions about spatial discovery could be verified with the computational results for saliency.

2. METHODS

2.1 3D Isovist representation

Conceptually, an isovist is a way of representing the amount of space that is visible from a particular vantage point. It is a geometric, and thereby measurable, representation of the experience of human sight. However, in practice the "visible space" that the isovist records is typically approximated to a horizontal slice, taken parallel to the ground at eye-height, through the 3D visible volume (Benedict 1979). Once the 2D isovist has been developed, then it is possible to quantitatively analyse its geometry to obtain various insights into the design properties of an architectural plan (Batty 2001; Turner *et al.* 2001). While 2D isovist analysis has dominated this field of inquiry, other researchers have set out to include the third dimension (Morello and Ratti 2009; Indraprastha and Shinozaki 2011). Such research seeks to capture the visual properties of an entire space from a defined location. However, inclusion of the third dimension poses particular challenges for two main reasons. First, when the early computational basis for isovist analysis was developed, CAD programs and 3D models were not yet readily available. Second, a high level of computational power is required for handling 3D design, data and processing. Thus, practical applications of 3D isovists have been rare because of both software and hardware limits.

Some previous attempts to analyse 3D isovists have adapted GIS based systems to define a viewshed as the set of grid cells in a Digital Elevation Model (DEM) that can be seen from a vantage point upon ray casting (Llobera 2003; Ratti 2005). Such approaches adapted approximate visibility analysis techniques to achieve computational efficiency. Other approaches to 3D isovist analysis include the development of a Spatial Openness Index (SOI); the ratio between the volume of the built structure and the area of the environment enveloping it (Fisher-Gewirtzman and Wagner 2003). Ultimately, 3D isovists offer a more realistic representation of the environment whereas 2D isovists have a more developed theory underlying their use and they are more computationally efficient. However, for the purpose of analysing spatial identity and wayfind-ability, the 2D variation is too abstract; it is effectively missing a large amount of the spatial information that is critical for determining saliency. Thus, to ensure both the accuracy and the usefulness of the method the present paper uses a computationally efficient, holistic model of 3D isovist generation and analysis. This is, in itself, a new technique that has not previously been used in architectural or urban analysis.

The construction method employed for the 3D isovists is based on an extension of two-dimensional ray-casting techniques to the third dimension. Ray casting in this context refers to the general problem of determining the first object intersected by a ray, in common terms this process is sometimes known as ray-testing. In this approach isovist rays are projected to cover the full 360° horizontal view orientation as well as a 0° to 180° vertical view orientation. The lengths of projected rays are recorded at each vantage point and combined together to form one isovist dataset. This projection is repeated at incremental eye height levels while maintaining the horizontal location of the vantage point. Thus, this method is akin to constructing a dense, vertically layered, series of three-dimensional isovists, collectively providing a computable three-dimensional isovist. Though other methods of information extraction, including direct mining from model data, are possible, the present variation of the traditional 3D ray casting approach more closely imitates human experience of space. Additionally, it caters for 3D space that is visible to humans belonging to different height or age groups (from children to adults or from short to tall), and thereby serves as a potential platform for future studies into the impact of architectural space on people of different heights. The variation of vertical view orientation between 0° to 180°, as opposed to the traditional 0° to 90°, is to ensure capturing both roof and floor features for indoor environments and the complete view-sphere to terrain for outdoor environments. Importantly, this modification ensures that the structural variations present on the floor and roof are all included in the saliency analysis. Through this process, the isovists are able to capture all features visible from any point in space and from any height above that point.

2.2 First person view for vantage point selection

The development of modern 3D visualization and design software has provided a hitherto before unavailable platform for the saliency analysis of architecture. However, the analysis of an interior, to identify and quantify salience, requires the computation of the properties of a majority of possible 3D isovists within a building, meaning that to be useful, a CAD model must be both accurate and minimal to ensure viable processing times. Thus, many of the standard CAD formats used in architectural practice are unusable for this purpose because they embed an excess of information into the geometric properties of the model. In response to this problem, the present research uses *Sketchup* (*Trimble Sketchup* 2012) to provide a simple 3D virtual experience of a design, that can be used to analyse and review any position in an architectural model. Effectively, using the virtual walk-through tool, a designer can open their model in Sketchup and navigate through it, to suggest the human experience of the design. In this study, the walk-through feature was used for the selection of vantage points. The user, by walking through and thereby exploring the model in a methodical way, records a series of coordinates, which locate their position along a path. Once the plan has been investigated the recording is stopped and the collection of coordinates that have been visited are indexed and they become the basis for the set of 3D isovist vantage points that are compared for salience.

2.3 Ray-casting and isovist generation

Vantage point recording within *Sketchup* is done using a Ruby plugin (Sketchup Ruby Scripts 2012) that offers a graphical user interface (GUI) to record the paths and register the spatial coordinates visited. Isovists at each vantage point and at different height intervals are then computed by the plugin using the ray-testing functionality available in the Sketchup Application Programming Interface (API). Figure 1 illustrates the view visible from particular points in the walk-through experience of the *Villa Savoye*. The figure also illustrates the manner in which the isovist rays are projected in horizontal and vertical directions. The computed ray lengths are stored in an array dataset while varying the azimuthal angle θ in horizontal direction and the polar angle Φ in vertical direction. The azimuthal angle is measured with respect to the y-axis whereas the polar angle is measured with respect to z-axis, at each vantage point. In order to organize and label the collected data, the isovist ray lengths are indexed as z_{ij}^{h}. The variable z represents the ray length, subscripts i and j represent values of azimuthal and polar angles respectively, and the superscript h represents the height of the vantage point. This way, the rays are indexed in the form of an easy to use array, or isovist array. When ray tracing is performed for indoor environments there are several additional factors that must be considered including how to treat openings (windows and doors) in the model. The results of ray casting at such openings can be interpreted in two different ways: *(i)* the ray should pass through the opening and reach out to a maximum ray length that is fixed; *(ii)* the ray stops at the opening and remains within the boundaries of the enclosed environment. For the present research the former interpretation is described as Fixed Length Isovists (FLIs) and the latter as Boundary Length Isovist (BLIs). The analysis performed on each of the isovist sets could produce totally different results. For example, consider the variance in the lengths of isovist rays in each azimuthal direction. In the case of BLIs, the major component of variance would be due to differences in the inner geometrical structure. Conversely, FLIs will have to account for a large amount of variance because of the sudden expansion of isovist ray lengths recorded through an opening. Depending on the location of the building under consideration, the view of the outside world could contribute as an attractive spot, or accounted as an area that does not offer much privacy. In this study, as we are analysing the inner structure and innate discoverability, the saliency detection is undertaken on BLIs alone.

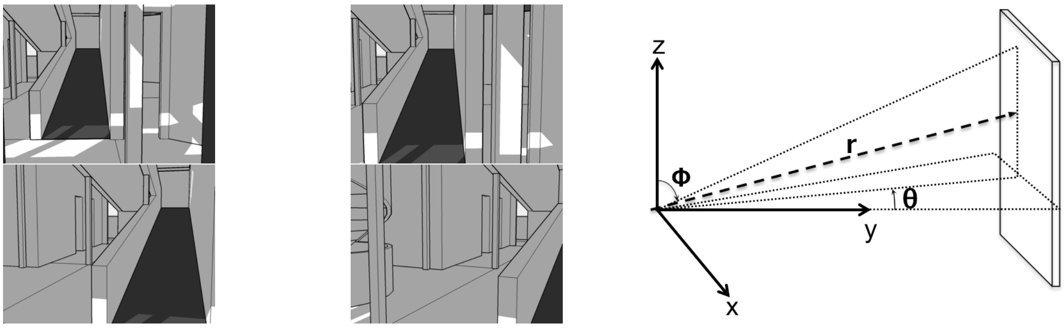


Figure 1: First person view of Google Sketchup with adjacent frames of vantage location recorded on Villa Savoye model (left). Isovist ray casting (right).

2.4 Isovist data visualization

The isovist array provides approximately 6.5 x 10^5 ray lengths for each vantage point. To obtain meaningful insights from this data it must first be categorised or segregated. There are two obvious ways in which the data can be segregated; one based on height and the other on polar angle. In the present research, the latter case is used. Here an isovist matrix containing 180 entries of ray lengths recorded for each polar angle (from 0° to 180° for each height, azimuthal angle pair), are reduced to one by computing their statistical summary. Various summaries for example, the minimum, maximum, mean, and variance, can be determined; these are called, respectively, Z_{min}, Z_{max}, Z_{mean}, Z_{var}. Mathematically, as an example $Z_{max} = \{\max_j z_{ij}^{h} : h \in [h_{min}, h_{max}], i \in [0,360], j \in [0,180]\}$. These Z matrices can then be visualized at particular height levels for a BLI (Figure 2). The figure represents Z_{max} and Z_{mean} (ordinate), observed at particular height and all directions of azimuthal angle (abscissa). The azimuthal angles range from 0° to 360°. The plot reveals that the Z_{mean} values are always significantly smaller than their corresponding Z_{max} values.

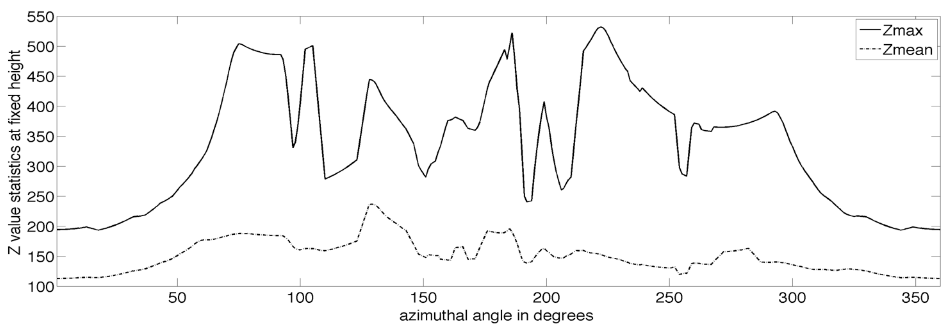


Figure 2: Z_{max}, Z_{mean} plot summarizing maximum and mean values of ray lengths over all polar angles observed at fixed height. The difference between mean and maximum values demonstrate that 3D isovist provide more detailed account of the environment section at the vantage point.

The advantages of producing a Z matrix are two fold. Firstly it reduces the data 180 times, secondly it can account for variations with changing eye height levels. This can be visualized by plotting the Z matrices in the form of a 2D heat map. In contrast to the previous example (Figure 2), which represents a single height isovist, the heat map reveals the summaries of ray lengths over all height levels. A heat map is a 2D matrix where each cell/pixel/unit of the matrix corresponds to one colour in the map with the lowest values corresponding to black and highest values to white. Figure 3 shows a heat map for a Z_{var} matrix and the associated view from its vantage point. The rows in the image correspond to different values of height (ordinate), and the columns correspond to values of azimuthal angle (abscissa). In this way, changes in the statistical summaries can be monitored by noticing changes in colour from top to bottom (for changes with height) and from left to right (for changes along azimuthal angle).

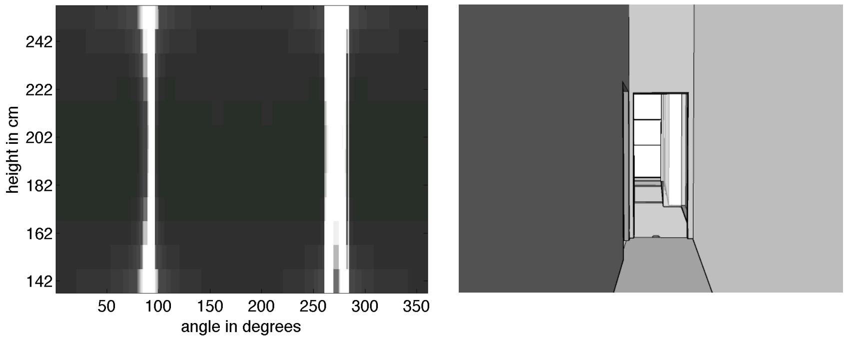


Figure 3: Heat map for Z_{var} (left), corresponding view at vantage point (right). Since the vantage point is located in a passage, there are only two directions where the isovist ray lengths have higher values; all other azimuthal directions have no contribution towards variance.

3. SALIENCY ESTIMATION

3.1 Principal component analysis

The proposed method for detecting salient regions is based on the technique of Principal Component Analysis (PCA) (Jolliffe 2002). The use of PCA on heat map data expresses ray length statistics in the form of a compact set of linearly uncorrelated vectors called principal components. It starts by computing the eigenvectors of the covariance matrix of the original heat map data and selects those eigenvectors that account for 95% of the variance present in the heat map. The numbers and indexes of such vectors are obtained by evaluating their respective eigenvalues. For example, let λ_i represent the eigenvalue corresponding to the i^{th} principal component. Then, let Λ be the sum of all eigenvalues, $\Lambda = \lambda_1 + \lambda_2 + \cdots + \lambda_{360}$. The percentage contribution towards entire variance by the i^{th} principal component (P_i) is therefore $(\lambda_i \times 100)/\Lambda$. In this study, it was observed that a maximum of six principal components were required to describe 95% of the total variance present in the heat map data. In combination, the extracted set of principal components from one heat map form a linearly uncorrelated set of vectors with each vector perpendicular to all others. This set is known as Principal Component Subspace, or simply subspace. The process of comparing subspaces obtained over different heat maps of the Z_{var} matrix forms the basis of saliency detection in this paper. Different measures are used to compare these subspaces amongst each other and measure how each subspace is different from others in a given set. These measures stipulate a number between zero and one, wherein zero denotes minimum difference and one denotes a completely different subspace. The comparison reveals the extent to which one subspace is different from others, thereby suggesting a method for identifying the subspace and hence the location that is most different from all others in a given set.

3.2 Comparison methodology

The spatial coordinates recorded during the walk performed within Google Sketchup comprise a series of ordered vantage point coordinates. These vantage point coordinates are indexed for easy reference, and corresponding to each index, the isovist matrix, Z_{var} matrix, its heat map and finally the principal component subspace is computed. Therefore, to address a vantage point and its associated view and data, its index is used and a correspondence between the index and vantage point location is maintained together in a set labelled as $\sum$. Based on this setup, a comparison between the subspaces can be performed in two ways. *(i)* Comparison between one subspace and all other subspaces present in $\sum$, we call this Global Saliency *(ii)* Comparison of one subspace Γ from a vantage point P with subspaces belonging to a subset of $\sum$, obtained by gathering subspaces from the vantage points recorded in a small section of the environment centred at P. We call this the Local Saliency of a vantage point. Global saliency values measure the uniqueness of locations relative to every other location in the environment; thereby revealing locations in the environment that are structurally different from all others. On the other hand, local saliency values provide relative uniqueness of a location in comparison to neighbouring locations. To compute global saliency, the entire subspace dataset is used and the comparison is performed taking one subspace at a time. On the other hand, for local saliencies the entire subspace dataset is divided into small sets (dividing the whole area of environment into smaller regions) containing subspaces corresponding to all vantage points recorded within that region. We adopt the term "section" as the location associated with one recorded vantage point, and the term "region" as a collection of neighbouring *n* sections. As an example, local saliency computed on a dataset containing 50 "neighbouring" vantage points can be used to identify the most salient section relative to those 50 sections. Since in this study vantage points are at least 20 cm away from each other (described in section 4), a comparison of 50 sections would effectively compare vantage points located in a 10-meter distance span.

3.3 Saliency measures

The saliency measures used in this paper examine the difference between two principal component subspaces each comprising a linearly independent set of principal components. For example, consider two isovist vantage point indices G and H, let their principal component subspace for the Z_{var} heat map be *L* and *M*. Let each subspace contain *i* and *j* principal components. Therefore the corresponding subspaces will have $(360 \times i)$ and $(360 \times j)$ dimensions respectively.

Angle between subspaces

The first saliency measure employed in this paper compares the angle between these two subspaces. It is derived from the similarity factor defined by Krzanowski (1979) who developed a method to measure the similarity between two principal component subspaces. For the present application, the complement of this measure was used to quantify the difference between two subspaces *L* and *M*; a difference denoted as S_{GH}. The subscripts G and H denote the indices of vantage points whose heat maps are currently being compared. Similarities between subspaces are defined, following Krzanowski (1979) as: $Similarity = trace(L^T MM^T L)/k$. In this definition, is it assumed that both subspaces *L* and *M* have the same number of principal components viz. *k*. For our application, this definition is modified to allow two subspaces having different numbers of principal components. Let $K = (i + j)/2$, the saliency measure, S_{GH}, is then computed as the inverse of the similarity, defined in equation 1. S_{GH} represents the inverse of the squared values of the cosine of the angles between each vector of the two principal component subspaces *L* and *M*.

$$S_{GH} = \frac{K}{trace(L^T MM^T L)} \tag{1}$$

Entropy of subspace

Entropy (Shannon 1948) provides an account of the informative content of a dataset. The second measure of saliency used in this work is defined using the entropy of the principal component subspace. Consider, for example, a heat map matrix for an isovist at vantage point index *G*, and its corresponding subspace *L*. Let the subspace consist of *i* principal component vectors. To compute the entropy of this subspace, first we compute the histogram of the values of coefficients of each principal vector contained in the subspace using a suitable interval size. The entropy for this subspace is then computed on the counts present in each histogram interval. Thus, let p_i represent the i^{th} interval, and let m be the total number of intervals present, then the entropy E_G for the isovist *G* is defined in equation 2. The values of E_G are scaled between zero and one. The higher E_G value for a vantage point index located in a region reveals the maximum uniqueness of the associated section, as compared to other sections within the entire region.

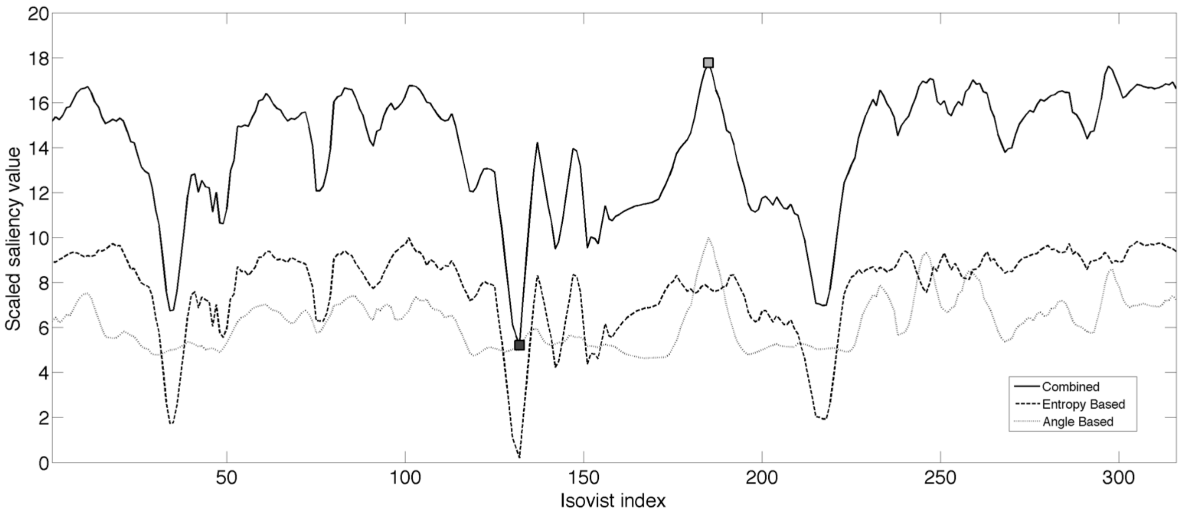
$$E_G = -\sum_{i=0}^{m} p_i . \log(p_i) \tag{2}$$

4. EXPERIMENTS AND RESULTS

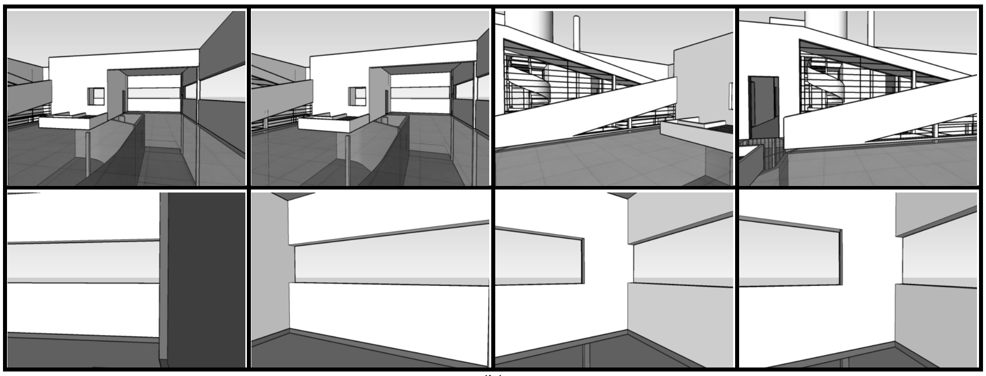
This section describes the experimental setup used to compare locally and globally salient regions present in the Villa Savoye model using the previously presented methods. In total 300 BLIs were generated using the ruby plugin in combination with the "walk" tool in *Sketchup*. The plugin selects the vantage points while ensuring that adjacent vantage points are at least 20 cm apart from each other. On the selected vantage points, isovists with different height levels (10 cm above floor to 110 cm, or the highest possible value) were computed. The height value was recorded with respect to the ground level to avoid confusion between different levels of the building/model. To ensure that a high level of detail was maintained during the recording process, a resolution of 1° of polar and azimuthal angles was selected. For local saliency computation, two experiments were performed. First by dividing the entire environment into three regions each containing 100 sections, and second by dividing it into six regions each containing 50 sections. Each of the sections was associated with recorded vantage points locations. Global saliency was computed over the entire dataset, considering one section at a time. The entire isovist dataset was generated on a Windows-based desktop PC with 16 GB RAM, and equipped with Intel Core i7 processor, running Sketchup and the additional plugin. Final computations of principal components, and salient regions were performed in MATLAB™ R2011. The generation of isovists at each height level in Sketchup took an average of one minute per vantage point, taking around 5 hours for the entire dataset generation. MATLAB™ scripts for computation of principal components (including importing data, computation and saving the principal components) took an average of 7 seconds per vantage point. Thereby taking an additional 30 minutes to complete the generation of the principal component space. Finally, the comparison of the isovists for saliency only took 10 minutes for the entire dataset. These timings confirm that this method is computationally efficient and can be used on any desktop computer capable of running CAD software.

4.1 Global saliency results

The saliency measures, when used to consider an individual vantage point, revealed the relative saliency of its associated location in comparison to the entire environment. A comparison of global saliencies using the two measures and the combined saliency are illustrated in figure 4a. The plot reveals the vantage point indices on the x-axis and scaled values of independent and combined saliencies on the y-axis. The indices of vantage points are in accordance with the order of recording performed. Each index represents one vantage point location and it can be used to retrieve the view observed in the model. The highest saliency was found between the 176th and 181st index (grey mark) and the lowest saliency was found between the 130th and the 132nd index (black mark). Views around these corresponding indices are also shown in figures 4b(top) and 4b(bottom) respectively. Figure 4c shows the corresponding Z_{var} heat maps for isovists with the highest and lowest saliencies. Observing the heat maps, it is evident that the region with higher saliency had large numbers of variations in the geometric structure in comparison with those of the lowest saliency value. Although the saliency values were also high at other indices, for the present paper only the one with maximum saliency is shown in the figure. The higher levels present at other locations are also potential indicators of the overall structural diversity present in the interior of the Villa Savoye, which previous scholars have argued is important for appreciating it spatially (Unwin 2010).



(a)



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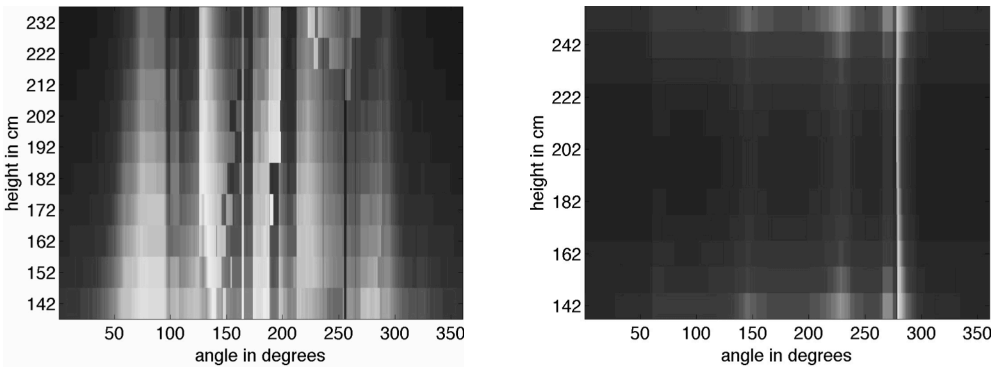
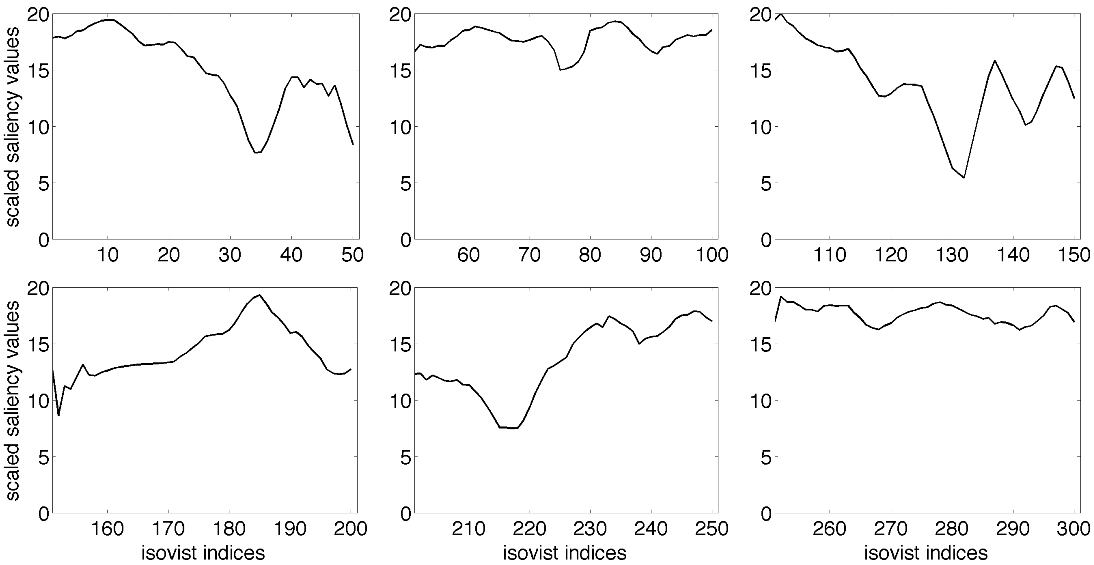


(c)

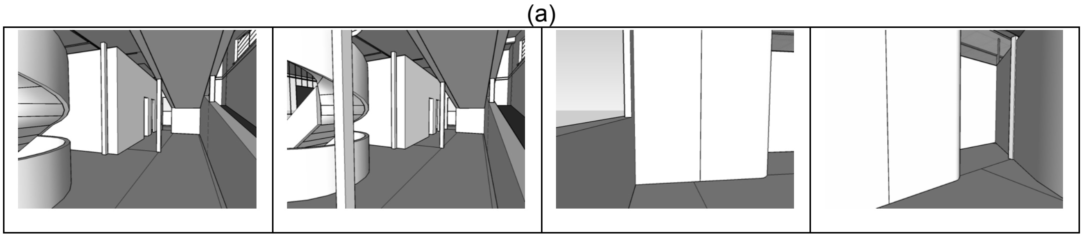
Figure 4: (a) Global saliency levels for all isovist indices. (b) Views from vantage point with highest saliency (row 1) and lowest saliency value (row 2). (d) Z_{var} heat maps of most salient (left) and least salient (right) vantage points.

4.2 Local saliency

Comparison of the local saliency can be performed on a local region of the environment. For the first experiment, the environment was divided into six regions, each containing 50 sections ordered in accordance with the recording performed. In a similar way to the representations used for results of global saliency, figure 5a shows the combined saliency values of each isovist index computed over the entire region containing 50 sections or vantage points. The abscissa points to the isovist index and the ordinate shows the combined saliency values. Examples of locally most and least salient locations present in the first region are shown in figure 5b, two views each of the most salient (left) and least salient (right) regions are shown. In second experiment, the environment was divided into three regions each containing 100 sections. Figure 5c displays the saliency values obtained in the second experiment.



(a)



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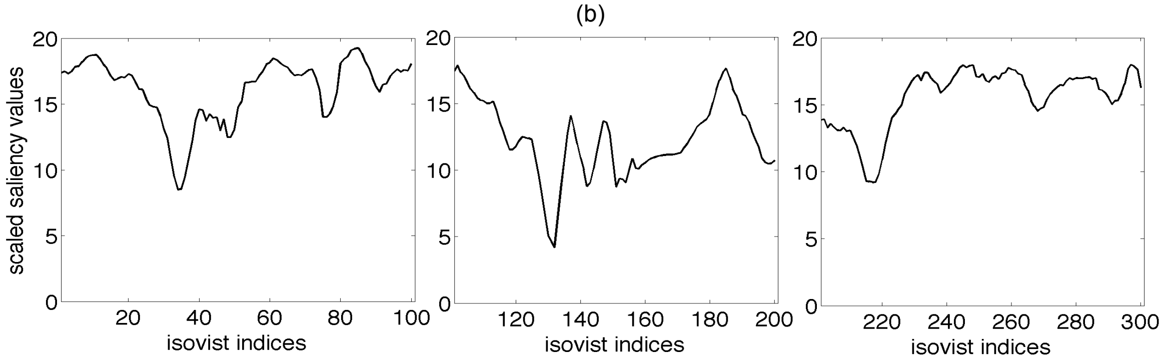

(c)

Figure 5: (a) Local saliency values with region constructed by taking 50 sections, (b) Most salient (left) and least salient (right) sections in first region, (c) Local saliencies for region constructed by taking 100 sections.

CONCLUSION

The present study uses a new, stable and repeatable process for generating 3D isovists to provide a unique methodology for measuring visual salience in an architectural environment. Using a statistical approach to processing data obtained from different sections of an architectural model, the paper compares this data using PCA and entropy to reveal differences in spatial structure of each section. This process is then used to measure relative saliency. The methodology is capable of being altered in multiple ways although the variation demonstrated using isovist ray lengths produces consistent and useful results. Future developments of this research will consider the inclusion of colour variations along with a version of the pure geometrical methodology for saliency computation. Finally, while neither comprehensive nor specifically for this purpose, the results of the saliency analysis of the Villa Savoye do broadly correlate with several previous interpretations of the spatial identity of this building. Such readings suggest that certain elements, like the spiral staircase and the roof terrace contain a high level of specific spatial information and are thus salient or landmark locations (Figure 4b, top and 5b, right) while others are more uniform or undifferentiated (Figures 4b, bottom and 5b, left).

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