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# A Taxonomy of Object/Building Oriented Viewpoint Selection Methods in Architecture: A Systematic Review

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## Abstract

This study systematically examines 3D viewpoint selection techniques, focusing on object- and building-oriented methods. The research aims to fill the research gap created by the fact that different disciplines in literature (computer graphics, architecture, and urban planning) have addressed viewpoint selection in isolation, and to integrate these methods under a holistic taxonomy. Conducted in accordance with PRISMA guidelines, the methodology involved a search of the Web of Science, Scopus, and Google Scholar databases covering a broad time span from 1988 to 2025. The search utilized the keywords "viewpoint research method", "viewpoint selection algorithms/methods", "classifications of viewpoint selection methods" and "viewpoint selection"; out of over 7,000 sources, 38 foundational studies with the highest methodological suitability were included in the detailed analysis. The methods were classified into six main categories: geometric, aesthetic, visual features, semantic, deep learning, and architecture/urban model based. The findings indicate that geometric and entropy-based methods dominate in object-oriented approaches, while GIS (Geographic Information Systems)-based spatial analyses and GPU-accelerated real-time visibility calculations take precedence in building-oriented approaches. The analytical value provided by this proposed classification lies in its clearly identifying the most appropriate computational strategy for each domain by differentiating methods based on the scale of application (from individual objects to urban fabrics). This study contributes to literature by providing a fundamental reference point for viewpoint determination systems in hybrid fields such as smart cities and interactive digital museology.

***Keywords:*** *Architectural visualization, Holistic taxonomy, Systematic review, 3D scene analysis, 3d viewpoint selection*

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## INTRODUCTION

Viewpoint selection is the process of determining the most appropriate camera position and orientation within a three-dimensional (3D) scene or object to maximize visual clarity, information transmission, and aesthetic value. This concept is of critical importance in many different disciplines, such as computer graphics, scientific visualization, architectural design, urban planning, photography, and museology. Presenting complex 3D data which is difficult to comprehend in two dimensions from the correct viewpoint reduces visual clutter, enhances data reliability, and strengthens the user's spatial perception. In this context, viewpoint selection methods documented in literature are discussed in chronological order.

In the early stages of technological development, researchers often used geometric methods to evaluate viewpoints. By examining the quantity of minimally degenerate faces in orthogonal projection, Kamada and Kawai adopted a methodology (Kamada & Kawai, 1988). To get goodness viewpoints, Roberts and Marshall used the morphological graph method (Roberts & Marshall, 1998). Kamada's method was refined by Plemenos & Benayada (1996), who also suggested a good view measurement based on projected area. A novel approach to virtual camera location based on scene visibility and viewpoint quality was put forth by Fleishman (Fleishman et al., 2000). Barral created an algorithm that uses the best viewpoints to automatically direct the camera through a 3D scene (Barral et al., 2000).



These have led to the creation of some effective methods, including the viewpoint entropy method by Vázquez et al. (2001), the silhouette stability method by Gooch et al. (2001), the mutual information theory, viewpoint, information theory-based shape analysis algorithm by Feixas (2002) and Page et al. (2003), and the graph-based image segmentation method for viewpoint exploration by Felzenszwalb & Huttenlocher (2004).

In 2005, several new techniques emerged because of advances in information theory and visual perception. Katz et al. (2005) proposed a mesh segmentation algorithm based on feature point extraction, Lee et al. (2005) proposed a mesh saliency method, Plemenos et al. (2005) proposed a relative entropy method and Polonsky et al. (2005) proposed an inductive method for viewpoint selection.

The mesh saliency and mesh segmentation technology also deeply affected viewpoint calculation. Attene et al. (2006) conducted a comparative study on the grid segmentation algorithm, Shilane & Funkhouser (2007) analyzed the special region of 3d surface. Fu et al. (2008) conducted research on 3D object posture and position in relation to viewpoints. Laga (2010) developed a semantic-driven approach to automatically choose the optimal viewpoint of a 3D object, and Vieira et al. (2009) developed an intelligent viewpoint learning method for 3D scene understanding. In addition, The Leibler (vSKL) distance method was used to measure viewpoint significance (Serin et al., 2011), and Biedl

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et al. (2011) adopted an efficient viewpoint selection method that used a convex polyhedral silhouette.

Network saliency and region of interest have gradually attracted the attention of scholars after 2011. Han et al. (2014) researched a saliency-based viewpoint selection method, Serin et al. (2013) used representative images to select the best viewpoints and segmentation, and Leifman et al. (2016) proposed a viewpoint selection method based on region of interest. A new avenue for viewpoint research was made possible by Xing's heuristic algorithm for surface reconstruction based on visual perception (Xing et al., 2013).

With the development of deep learning, after 2014, viewpoints research also tends to use neural networks. Su et al. (2015) used 3D models to train the convolutional neural network (CNN) for the viewpoint estimation, Francisco Massa et al. (2016), designed a multi-task CNN to realize viewpoint estimation. George Leifman et al. (2016), selected viewpoint clusters based on the visually interesting part of the network, while Jeong & Sim (2017) used a semi-regular grid to find a saliency region. Multi-viewpoints also garnered interest. To accomplish a recursive estimation in 3D scene reconstruction, Engler & Wuensche (2017) employed multi-pair virtual cameras. A method for correlation, retrieval, and reconstruction in large-scale 3D scenes based on numerous views was created by Rahul Sawhney et al. (2018).



Regarding the building-focused viewpoint, the central focus of the study is the skeleton line extraction method, a widely used GIS technique that forms the basis for viewpoint selection, was employed (Chen & Qian, 2022; Lewandowicz & Flisek, 2020). In addition, the Efficient Precise Viewpoint Selection (EPVPS) method (Tang et al., 2025), which aims to select the optimal viewpoint for the maximum field of view within a given area, was applied. The starting point for the method, which offers a multi-viewpoint option, was the Empty Circles-based K-means (ECKM) technique (Biswas et al., 2023; Ikotun et al., 2023). Similarly, methods such as intelligent systems capable of performing image analysis from multiple viewpoints (Ma et al., 2023; Civicioglu & Besdok, 2024), Apache Spark's multi-level distributed technology (Dong & Zhang, 2023), and GPU parallel computing capabilities (Xiao et al., 2024) are also among the techniques used.

Early studies in literature are generally object-oriented and focus on the visibility of objects in architectural spaces and the selection of the optimal vantage point. Current approaches, however, generally focus on specific application areas (computer graphics, architectural viewpoint selection methods, or GIS-based urban analyses). These methods, which have been used from the past to the present, have not been addressed holistically within an interdisciplinary framework. This situation prevents the establishment of a methodological bridge between objects on the micro scale and urban buildings on the macro scale. This gap in the existing literature constitutes a fundamental research gap that makes it difficult for researchers to select the most appropriate method for different scales and objectives.

This study was conducted to address this research gap and to consolidate the methods scattered throughout the literature under a systematic taxonomy. With the advancement of technology (such as deep learning, smart cities, and interactive museum applications), the need for viewpoint determination systems is growing rapidly. The primary objective of this study is to bring together methodological approaches from different disciplines under a common terminology, thereby providing a comprehensive and practical reference point for future research. Accordingly, the objective of this study is to classify 3D viewpoint selection techniques into two main categories object-oriented and building-oriented strategies and to highlight the analytical value of these methods.

Within this framework, the study seeks to answer the following key questions:

**RQ1:** How can the 3D viewpoint selection techniques in literature be systematized under object-oriented and building-oriented paradigms?

**RQ2:** What are the key methodological differences between object-oriented and building-oriented approaches, and in which areas do they each have an advantage over the other?

**RQ3:** In this process, which spans from traditional geometric methods to modern deep learning models, what are the current approaches that yield the most effective results at the architectural and urban scales?



To classify viewpoint selection methods within this scope, comprehensive research was conducted through a building literature review on articles from different disciplines, theses on the subject, book chapters, algorithms written for method improvements, tools used and methods developed. Based on the data obtained, the methods were categorized into two main groups according to their focus, the types of solutions they offer, and the types of tools and data they use. The main object-oriented and building-oriented approaches are also divided into six headings according to the type of system they are based on. These headings are elaborated on topics such as information production methods, visual perception patterns, deep learning techniques, aesthetic concerns, and urban and architectural connections. Viewpoint selection methods, which are handled with an interdisciplinary approach, offer solutions that can be integrated into different areas of use with developing technological systems.

## A METHODOLOGICAL OVERVIEW of VIEWPOINTS

The methodologies were organized into two principal categories predicated on their focus and the nature of the data utilization:

**Object-Oriented Methods:** These methodologies ascertain optimal viewing angles through the examination of an object's geometric properties, visual characteristics, or semantic representations.

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**Building-Oriented Methods:** These methodologies are employed in contexts such as urban environments or architectural buildings, wherein viewpoint selection is contingent upon spatial data, visibility assessments, and patterns of user mobility. Within each primary category, subcategories were delineated based on their fundamental strategies (e.g., geometric analysis, entropy assessment, visual attention modeling, machine learning applications, GIS-based techniques). Furthermore, implementation tools and software, including MATLAB, ArcGIS, OpenGL, or neural network frameworks, are documented to identify common development trends.

## DATA ANALYSIS

This study is a systematic review and taxonomic classification examining object- and building-oriented 3D viewpoint selection techniques. In accordance with the PRISMA guidelines for systematic reviews (Page et al., 2021; Rethlefsen et al., 2021; Elsman et al., 2024; Torre-López et al., 2024), methods for selecting the optimal viewpoint have been classified in the fields of architecture, urban planning, photography, museology, and object design.

For a systematic review and taxonomic classification, we conducted a search in the Web of Science, Scopus, and Google Scholar databases covering studies from 1988 to 2025 using the keywords “viewpoint research method”, “viewpoint selection algorithms/methods”, “classifications of viewpoint selection methods” and “viewpoint selection.” The sources obtained from this search are presented in Figure 1.



After rigorous screening for relevance, age, accessibility, and methodology, we processed 1,079 WOS sources (excluding 422 irrelevant, 75 old/inaccessible/unclassified), 2,862 Scopus sources (excluding 296 duplicates, 1,059 out-of-scope, 1,024 for other reasons), and 3,490 Google Scholar sources (excluding 1,840 off-topic, 1,482 for inaccessibility/duplicates/outdated technology). The reasons for excluding “outdated” or ‘inaccessible’ sources are detailed as follows:

- **Age Criterion:** Studies published before 1988, as well as “obsolete technologies” that do not form the basis for current 3D computing environments, digital spatial analyses, and modern rendering technologies, have been excluded.
- **Accessibility Criterion:** Sources for which the full text is not accessible via institutional databases or that do not contain sufficient methodological data for classification have been excluded to ensure the reliability of the analysis.

- **Methodological Suitability:** Studies that remain purely theoretical and do not present an applicable algorithm or mathematical model have been excluded from the scope.

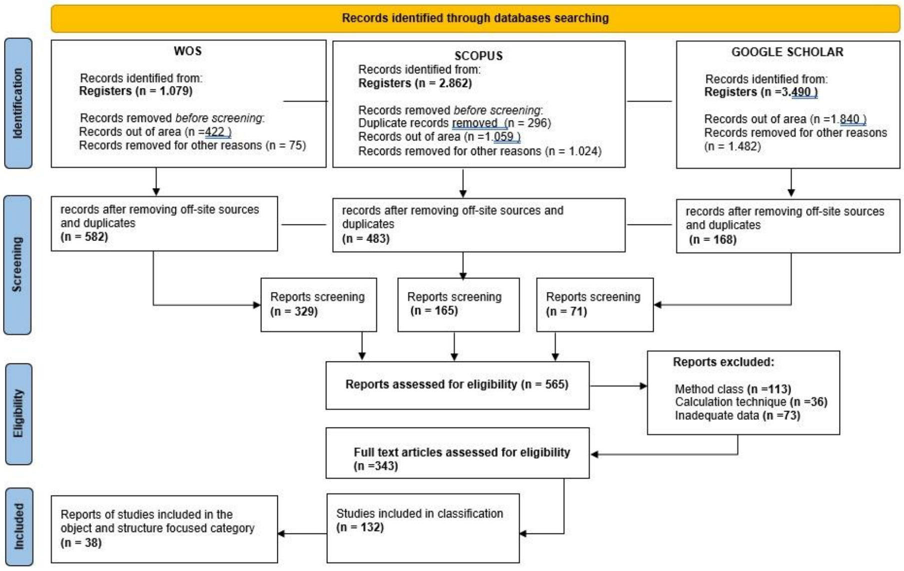


**Figure 1.** Process for systematic review and taxonomic classification of object and building-oriented viewpoint selection methods (sourced by authors)

Based on these criteria, the number of sources was reduced to 565. The process of narrowing down the remaining sources to 38 is as follows, step by step:



**1. Initial Classification:** As a result of preliminary screenings based on abstracts, methods, and research fields, 565 sources (329 WOS, 165 Scopus, 71 Google Scholar) were identified.

**2. Method and Technical Filtering:** In this stage, 113 sources were excluded due to inconsistency in method classification, and 36 sources were excluded due to insufficient computational techniques.

**3. Insufficient Information Screening:** During the review, an additional 73 sources that did not provide detailed data were excluded, and 343 full-text articles were selected for detailed analysis.

**4. Taxonomic Focus:** While 132 of these texts contributed to general classification, the 38 core studies presented in Table 1 were selected as those with the "highest methodological suitability," as they directly provided methodological data and algorithms for object- and building-focused approaches.

In addition, the screening and coding processes for this study were conducted independently by the authors, and any disagreements were resolved through joint review.

## SYSTEMATIC LITERATURE REVIEW

In the study, viewpoint selection methods and algorithms including object-oriented and building-oriented approaches (Table 1) were classified into six main categories under method-specific subheadings. This table forms the framework of the taxonomy and explains why the selected 38 sources were considered "core sources" by highlighting the specific algorithms and methods they present.

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**Table 1.** Viewpoint selection methods and algorithms using systematic review method (sourced by authors)

| Source | Method / Algorithm | Explanation |
|---|---|---|
| **Kamada, T.& Kawai, S. (1988)** | Method based on geometric knowledge | The least number of degenerate faces in the orthogonal projection is examined as part of a methodology. |
| **Roberts, D.R. & Marshall, A.D. (1998)** | morphological graph method | A description of the object's model and the visibility of its faces serve as a planning system for choosing viewpoints. |
| **Plemenos, D. & Benayada, M. (1996)** | Method based on the projected field | Plemenos and Benayada developed Kamada's method and proposed a measure of opinion. |
| **Fleishman, S.et al. (2000)** | Based on quality of viewpoint | A novel method for virtual camera placement based on scene visibility and viewpoint quality was presented by Fleishman. |
| **Barral, P.et al. (2000)** | Use of virtual camera based on 3D scene visibility | Barral developed an algorithm that automatically moves the camera through a 3D scene by utilizing the best viewpoints. |
| **Vázquez, P. P.et al. (2001)** | viewpoint entropy method | To calculate entropy, a probability distribution function must be used. |
| **Gooch, B.et al. (2001)** | silhouette stability method | To determine the format, viewpoint, and arrangement of a picture of a three-dimensional object, a method based on heuristic composition rules is described. |
| **Feixas, M. F. (2002)** | mutual information theory | The degree of correlation or dependency among all points or components of a scene is known as mutual information. |
| **Page, D. et al. (2003)** | information theory-based shape analysis algorithm | A method for calculating shape information for 3D triangular meshes and 2D planar contours is introduced. |
| **Felzenszwalb, P. F.et al. (2004)** | graph-based image segmentation method | One important aspect of the method is its ability to preserve detail in low-variability image regions while ignoring detail in high-variability image regions. |
| **Katz, S., Leifman, G.et al. (2005)** | a mesh segmentation algorithm based on feature point extraction | The algorithm presented here generates hierarchical segmentations into meaningful components of orientable meshes. |
| **Lee, C. H.et al. (2005)** | method of mesh clarity | Low-level cues from the human visual system served as the inspiration for the salience concept. |
| **Plemenos, D., Sbert, M.et al. (2005)** | relative entropy method | The method is based on selecting the view that minimizes the Kullback-Leibler distance between the mixture of the distributions of all selected viewpoints and the actual field distribution. |
| **Polonsky, O.et al. (2005)** | An inductive method | The descriptors of the model consist of 3 principles: a descriptor based on an accepted measure of geometric complexity for a 3D shape, a descriptor based on inherently appearance-dependent features, and a descriptor that assigns values to some semantic part of the model. |
| **Attene, M.et al. (2006)** | grid segmentation algorithm | The main idea of the algorithm is to first find meaningful components while keeping the boundaries between components fuzzy. |
| **Shilane, P.et al. (2007)** | shape-based surface separation calculation | Shilane analyzed a specific region of the 3D surface. |
| **Fu, H., Cohen-Or D.et al. (2008)** | A supervised learning approach on orthogonal orientation of 3D model | Fu has studied the location and pose of 3D objects in relation to viewing angles. |
| **Serin, E., Doger, C.et al. (2011)** | distance method | Viewpoint importance was assessed using the Leibler (vSKL) distance approach. |
| **Vieira, T.et al. (2009)** | Learning approach with support vector machines | Vieira, Laga, and Biedl used a convex polyhedral silhouette as an efficient viewpoint selection technique. |
| **Leifman, G., Shtrom, E.et al. (2016)** | A viewpoint selection method based on interesting region | The technique suggests a novel approach for identifying surface areas of interest. |

| | | |
|---|---|---|
| **Serin, E.et al. (2013)** | Greedy view selection integrated vSKL | Serin used representative images to select the most appropriate viewing angles. |
| **Han, H., Li, J.et al. (2014)** | a viewpoint selection method based on significance | Han suggested a novel approach to saliency segmentation-based view selection. |
| **Xing, L.et al. (2013)** | efficient remeshing framework | Xing's surface reconstruction based on visual perception was made possible by the heuristic algorithm. |
| **Su, H.et al. (2015) and Shi, N.et al. (2019)** | Convolutional Neural Network (CNN) | A convolutional neural network (CNN) for viewpoint estimation was trained using 3D models. |
| **Massa, F.et al. (2016)** | CNN based algorithm for systematic foundation design selection | For viewpoint estimation, Francisco Massa created a multitask CNN. |
| **Leifman et al. (2016)** | Surface interesting region detection with triangulated mesh model | The visually appealing area of the mesh is used to choose viewpoint clusters. |
| **Jeong, S. W.et al. (2017)** | a unified detection algorithm saliency for three-dimensional mesh models | Jeong used a semi-regular grid to find a saliency region |
| **Engler, T.et al. (2017)** | feature based sparse stereo algorithms | Torsten used multi-pair virtual cameras to perform a recursive estimation on 3D scene reconstruction. |
| **Sawhney, R.et al. (2018)** | macro-scale 3D structural geometry approach | A method for correlation, retrieval and reconstruction in large-scale 3D scenes based on multiple views is established. |
| **Chen, G.et al. (2022) and Lewandowicz, E.et al. (2020)** | skeleton line extraction (GIS algorithm) | Two well-known methods for vector data skeleton line extraction that depend on image processing technology are enhanced constrained Delaunay triangulation (CDT) and raster data skeleton line extraction. |
| **Tang, G.et al. (2025)** | Multiple Viewpoint Selection Method | Efficient Precise Viewpoint Selection (EPVPS) algorithm is utilized. |
| **He, J., Zhou, W.et al. (2016)** | Riemannian metric | Once this metric is established, individuals' preferences regarding viewpoints are effectively validated through K-medoids clustering. |
| **Llobera, M. (2003)** | Multipoint Field of View Analysis Method (GIS based) | The algorithm used in digital elevation model (DEM) based field of view analysis was utilized. |
| **Deinzer, F.et al. (2006)** | A viewpoint selection method based on reinforcement learning | A merging approach based on the Condensation Algorithm is used. |
| **Gu, C.et al. (2019)** | deep metric learning method | An object-centered viewing sphere with a constant radius is proposed. |
| **Hosseininaveh, A.et al. (2021)** | Imaging Network Design Method | A new photogrammetric approach to imaging network design is proposed. |
| **Shirani-Mehr, H.et al. (2009)** | PTD (participatory tissue documentation) method | PTD is implemented in two steps: viewpoint selection and viewpoint assignment. |
| **Neuville, R.et al. (2019)** | Flythrough creation algorithm (FCA) | A theoretical and operational method for automatically determining the best viewpoints to control congestion is described. |

## CLASSIFICATION OF VIEWPOINT RESEARCH METHODS

According to the data obtained because of the literature review, viewpoint selection methods are classified into six categories. These categories are basically as follows:

1. based on geometric information (field)



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2. based on aesthetic information (surface curvature)
3. based on visual features
4. based on semantics
5. based on deep learning
6. based on architectural and urban models

**1. Methods based on geometric information**

These techniques evaluated viewpoint using measurements including curvature, silhouette, projected area, geometric area, etc. "General Position" theory: The idea of a "general position," which denotes a favorable viewpoint position, was first proposed by (Kamada et al.,1988). The extrinsic problem of projection direction vectors replaces the "canonical appearance" problem in the viewpoint.

**2. Methods Based on Aesthetic Knowledge**

**2.1. Viewpoint research based on artistic composition**

As a result of extensive studies, the foundations of the concept of the "golden section" were laid (Sander et al., 1932). Building on artistic principles, Feiner et.al. (1991) created images, while Kawai et.al. (1988) presented an automatic lighting reconstruction method based on artistic composition. Karp et.al. (1990) also developed a technique for generating animation sequences using artistic composition. Kowalski et.al. (2001) proposed a method to assist users in creating artistic pieces.

Gooch further advanced this area by developing a plan rooted in creative composition. This involved producing patterns using orthogonal projection and calculating them via a silhouette intensity procedure (Figure 2).



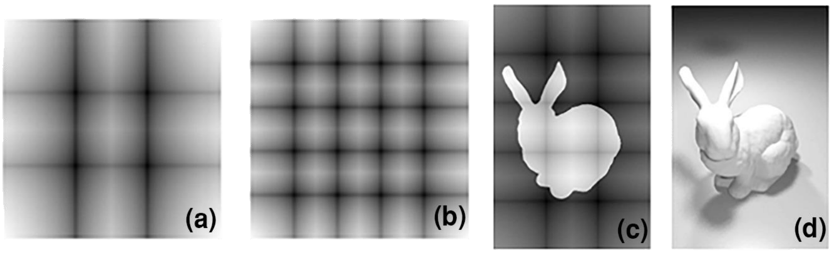


**Figure 2.** (a) The one-third rule of intuitive composition; (b) The one-fifth rule of intuitive composition; (c) layout template; (d) shaded result (Adapted from Gooch et al. (2001))

**2.2. Estimated area-based viewpoint method**

**Low Level Image Quality Assessment Method:** The strategy originated with Kamada and Kawai's "80-ties" method (Kamada et al.,1988). Plemenos & Benayada (1996) later proposed an approach based on the estimated visible surface area. Kamada's settings were later adjusted to maximize viewpoint projection by Barral and colleagues (2000). Plemenos & Benayada (1996) used the projected fraction of visible areas to assess visual quality.

**High-level viewpoint quality assessment method:** A low-level viewpoint quality assessment approach cannot cover a wide scene. Sokolov invented a high-level assessment method (Sokolov et al.,2006).

**2.3. Octree Based Viewpoint Selection Method**

Colin (1988) established an eight-tree building-based methodological framework for viewpoint selection. Building on this, Plemenos et al.

(1996) developed an iterative technique for autonomous viewpoint selection. This method centers on a spherical volume encapsulating the scene's spatial organization, with its surface representing all possible observational angles (Figure 3).

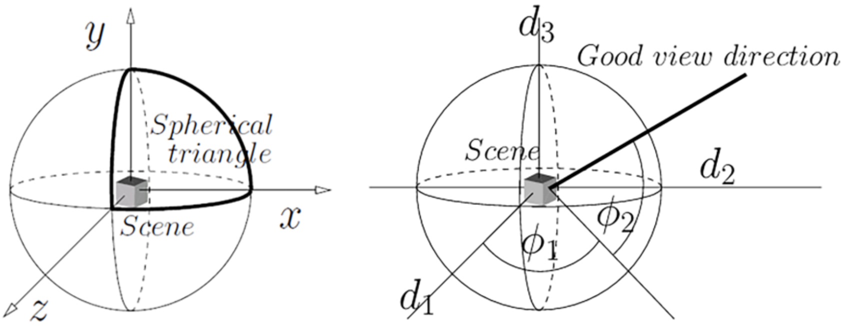


**Figure 3.** (a) A sphere divided into 8 global triangles - Octree method; (b) good direction of view (d1=d2=d3=The three most appropriate viewpoints

### 2.4. Method for assessing viewpoint quality based on information entropy

**Method based on viewpoint entropy:** A technique based on Shannon entropy was proposed by Vazquez & Feixas, who subsequently dubbed it the viewpoint entropy method (Vázquez et al.,2001). In particular, the entropy value is used to measure the projected fields as a unit of information.

**Method based on curvature entropy:** Page used silhouette and curvature to develop the viewpoint entropy approach (Page et al.,2003). The detail and depth information of the observations determined the curvature entropy. However, it has sometimes led to negative results when there are overly symmetric buildings.



**Method based on depth and silhouette entropy: Vázquez et al. (2001)** obtained silhouette entropy and depth entropy after observing 320 points of view. Warmer hues and larger dots indicate higher (better) values, which are the best viewpoints based on them (Figure 4).

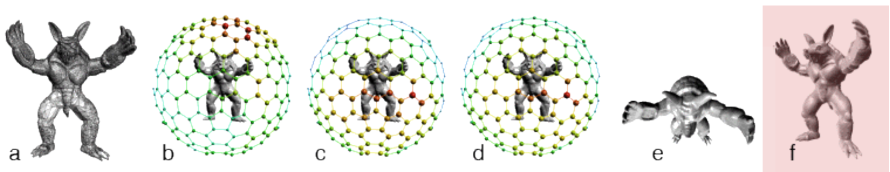


**Figure 4.** (a) Mesh; (b) Depth; (c) Silhouette; (d) Depth Silhouette; (e) Depth best; (f) Results: Best view (Adapted from (Vázquez & Andújar, 2007)).

**Other methods of information entropy:** Vazquez suggested a multiscale method based on the Gull & Skilling (1985) entropy because the Shannon entropy would result in certain intractable reduction issues.

### 2.5. Method based on Kullback-Leibler distances

Sbert proposed a viewpoint selection method based on the K-L Distance (Kullback-Leibler Distance) to find the fewest representative points of view (Sbert et al.,2005) (Figure 5).

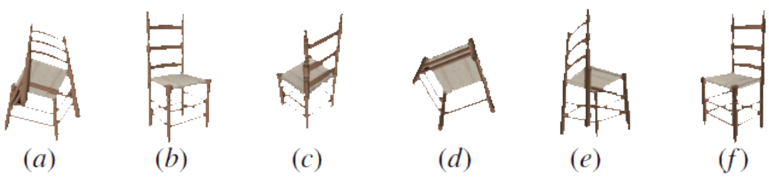


**Figure 5.** The six most representative views of the chair object selected by the KL algorithm (Adapted from (Sbert et al.,2005)).

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### 3. Methods Based on Visual Features

Techniques relying on visual aspects are primarily influenced by features such as volume, mesh salience, silhouette, and curvature. Feixas (2002) introduced a novel object recognition theory that has subsequently influenced numerous algorithms, including Mortara's semantic segmentation (Attene, Mortara et al.,2006), Shilane's saliency-region-based semantic viewpoints (Shilane & Funkhouser,2007), and Fu's vertical-direction-based characteristic semantic method (Fu et al.,2008). More recently, novel algorithms have emerged, such as Leifman's intriguing area-based semantic technique (Leifman et al.,2016), Sokolov's speculation-based selection method (Sokolov et al.,2006), and Chen's Schelling point-based method (Chen et al.,2012).

#### 3.1. Viewpoint assessment method based on visual perception theory

Loken (1984) posited that human visual perception integrates a scene holistically rather than as isolated elements. Kucerova et al. (2012) further explored this by combining Gestalt psychology and visual perception theory to evaluate viewpoint quality and the influence of human intuition in virtual tours.

**Visual Attention Model:** Stemming from research on early primate neural architecture and visual behavior, Itti et al. (2002) introduced the prominent "central containment mechanism," a method applied to linear center wrapping (Noser et al.,1995). Kucerova et al. (2012) presented three different approaches for selecting the best view of 3D objects: a geometry-based method (maximizing the number of visible vertices), a visual attention method, and mapping a 3D scene to a 2D image using entropy (Figure 6). They then compared these approaches using a questionnaire.



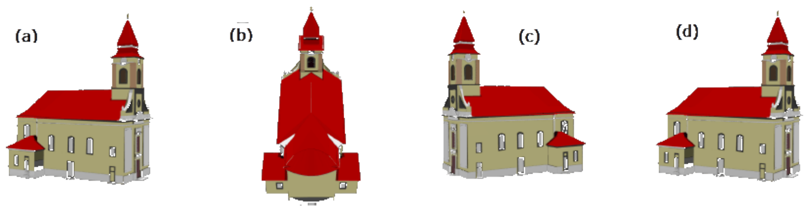


**Figure 6.** (a) Geometry based method; (b) Visual attention method; (c) Entropy based method; (d) Questionnaire (Adapted from (Kucerova et al., 2012)).

**Visual perception model based on visual preference:** Polonsky et al. (2005) pioneered the concept of standard view descriptors or viewpoint attributes, which can be integrated into a single measuring function. Expanding on this, Vieira et al. (2009) employed support vector machines to classify view descriptors for optimal viewpoint selection. Secord et al. (2011) developed a global measuring function by combining various view quality descriptors, categorized into five types: region, silhouette, depth, curvature, and semantic.

#### 3.2. Curvature-based viewpoint evaluation method

Barral & Noser used histograms to examine the visible surface's properties (Barral et al.,2000; Noser et al.,1995). Based on Barral's method, Sokolov proposed a viewpoint quality estimation method based on total curvature (Barral et al.,2006). Computing efficiency is increased by employing the "point-to-point" strategy rather than the "point-to-region" method.

**3.3. Viewpoint evaluation method based on viewpoint complexity**

Plemenos found a way to determine viewpoint complexity based on the quantity, size, orientation, and separation of discernible patches (Plemenos & Benayada,1996) .

**3.3.1. Histogram-based view complexity calculation**

Plemenos assigned a different hue to each patch to determine viewpoint complexity using a histogram approach. This approach might be used to calculate the scene's proportions of each color.

**3.3.2. Information theory-based computation of viewpoint complexity**

Viewpoint selection has been extensively studied across various disciplines, including volume rendering and object recognition, often leveraging an information theoretical framework.

In computer graphics, diverse criteria assess viewpoint quality. Koenderink & Doorn (1979) introduced the "view graph" in the 1970s to delineate viewing regions around objects. Arbel et al. (1999) proposed a measure of uncertainty for belief distributions, guiding online navigation with offline entropy maps. Following Vázquez et al.(2001)'s introduction of Viewpoint Entropy (VE), similar methods gained prominence, especially in volume rendering.



Jensen-Shannon Entropy (Cover & Thomas,1991; Blahut,1987), a core concept in information theory, quantifies the uncertainty of a random variable.

Viewpoint Entropy (VE), as asserted by Vázquez (2003), is a highly suitable factor for viewpoint selection. Consistent with Fleishman (2000), various metrics are compared, including basic ones like the number of correctly captured faces. Originally proposed by Vázquez et al. (2001), VE quantifies the information captured by a viewpoint, considering both projected area and face count. Rigau et al. (2002) developed a comparable metric for analyzing the visibility complexity of 2D scenes.

**3.4. Viewpoint selection method based on network salience**

Building on Koch & Ullman's (1987) concept of salience drawing visual attention, Itti et al. (1998) proposed an efficient center-periphery mechanism for salience calculation. Researchers have further explored visual salience through various methods: Tsotsos et al. (1995) utilized visual attention cues and attentional analysis, while Milanese et al. (1994) employed a nonlinear relaxation method to identify salient regions. Privitera et al. (1999) introduced an automatic pre-recognition approach for computing interesting regions and later proposed an automatic thumbnail cropping method based on image salience by extracting these regions. Chen et al. (2012) developed a visual perception model to modify visual attention space. Additionally, DeCarlo & Santella (2002) suggested a stylization technique for Suh et al. (2003), and Santella & DeCarlo

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(2004) used saliency areas to simplify networks and create abstract visuals.

### 3.5. Method of selecting viewpoints based on mutual information between viewpoints

Vázquez created an information network for viewpoint information and introduced a system for evaluating viewpoints (Vázquez et al.,2001). The VMI technique was able to aggregate the most representative viewpoints to get a suitable set of viewpoints with the least amount of mutual information. Figure 7 displays the six best images that the VMI algorithm generated.

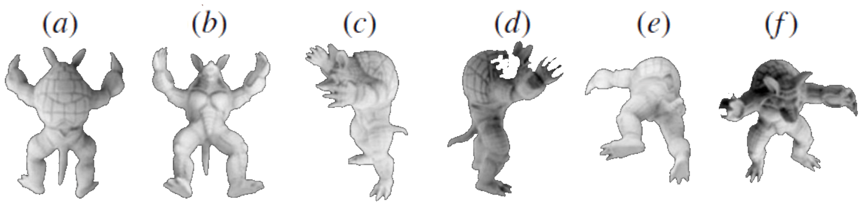


**Figure 7.** Six armadillo model views were chosen using the VMI technique (Adapted from (Bonaventura et al., 2018)).

## 4. Understanding-Based Viewpoint Selection Method

The semantics-driven approach to viewpoint selection utilizes semantic segmentation to evaluate viewpoints, incorporating scene semantics and synthetic labels as evaluation features. Attene et al. (2006) developed an efficient annotation method for virtual 3D objects using a hybrid segmentation approach that allows user input. Takahashi et al. (2005) proposed a feature-driven method to identify optimal viewpoints, integrating semantic information into an assessment function. Similarly, Mortara et al. (2009) used semantic features to calculate network saliency in specific orientations.

### 4.1. Semantic-based network segmentation

Polonsky positioned a semantic component of the model to maximize the visible projected area and identify the ideal view (Polonski et al.,2005). Mortara introduced a semantic segmentation technique that relies on aesthetic standards (Mortara & Spagnuolo (2009).

### 4.2. Semantically based viewpoint selection

Following the use of several unique viewpoints evenly distributed around the item, Mortara et al. (2004) developed an assessment function and thoroughly examined the scene's salience and semantic aspects. In a separate study by the same author in collaboration with other researchers, a set of viewpoints was defined on a viewing sphere surrounding the object. By applying the Loop subdivision scheme twice, an equal distribution of 162 viewpoints surrounding the shape was achieved (Mortara & Spagnuolo, 2009) (Figure 8).

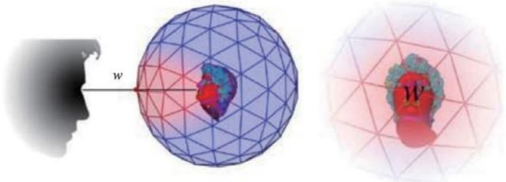


**Figure 8.** According to Mortara's definition, the viewing sphere: its vertices are the admissible viewpoints (Mortara & Spagnuolo, 2009).

## 5. Viewpoint Selection Method Based on Deep Learning

George Leifman chose points of view using the "Regions of Interest (ROI)" technique, which was put forth (Leifman et al., 2016). Leifman's algorithm is used to automatically select the most interesting collection of viewpoints for a mesh surface. The main steps are generating candidate viewpoints, calculating the Region of Interest (ROI) observed by each candidate, and optimizing this selection to improve its quality by selecting the viewpoint that provides the most information.

Leifman compared four conventional multiple viewpoint selection methods with this method (Figure 9). These four classic methods are Lee's et al. (2005) Mesh Saliency technique, Mortara's & Spagnuolo (2009) Semantics-driven Best View of 3D Shapes, Yamauchi's Towards a Stable and Salient Multi-view Representation of 3D Shapes (Yamauchi et al.,2006), and Secord's Perceptual Models of Viewpoint Preference (Secord et al., 2011).

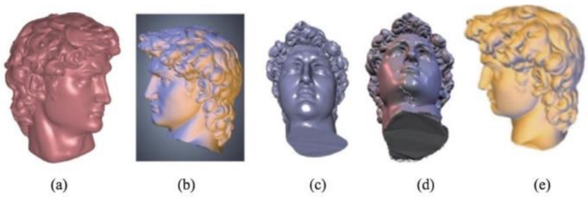


**Figure 9.** Comparison of Leifman's viewpoint selection algorithm with four traditional viewpoint selection algorithms (Adapted from (Leifman et al., 2016)).

## 6. Viewpoint Selection Method Based on Architectural and Urban Model

### 6.1. Method of Choosing a Viewpoint Suitable for Architectural Heritage's Visual Impact



A quantitative, GIS-based spatial analysis approach is used to select relevant viewpoints for assessing the visual impact of architectural history.

**Visual Impact Assessment**: Selecting appropriate viewpoints, also known as survey, observation, or sample points, is crucial for conducting quantitative visual impact assessments and evaluating dispersed areas (Mohseni et al.,2020; Zhao et al.,2020). The chosen viewpoints significantly influence the objectivity and accuracy of the assessment (Qi et al., 2013).

**Viewpoint Selection:** Methods for viewpoint selection vary; for example, Qi et al. (2014) and Xu et al. (2021) uniformly select sample points along circular routes, while Daniel (2001), randomly chooses assessment points along forest roads.

Skeletal line extraction is a common GIS technique underpinning viewpoint selection (Chen & Qian, 2022; Lewandowicz & Flisek, 2020). This method defines the central axis of geometric forms and is frequently applied to analyze stripe-like features in architectural heritage landscapes. While viewpoints are typically aligned with street or courtyard axes, larger areas may necessitate additional viewpoints along the central axis, often within the spatial boundaries of the courtyard's skeleton lines. The skeleton line's midpoint represents its central form, its endpoint signifies its origin, and its intersections indicate changes in direction.

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### 6.2. Viewpoint selection method based on multiple viewpoints

Terrain viewpoint selection aims to identify optimal viewpoints within a given area for maximum visibility. The Efficient Precise Viewpoint Selection (EPVPS) method (Tang et al., 2025) offers a valuable framework for multi-viewpoint planning. This method first employs the Empty Circles-based K-means (ECKM) technique (Biswas et al., 2023; Ikotun et al., 2023) to determine initial cluster centers for candidate viewpoints. Next, it introduces the Weighted Coverage Overlap Metric (WCOM), a new evaluation metric that quantifies visibility by segmenting the candidate points' field of view into overlapping and coverage contribution points. These results are then stored. Finally, the clusters of coverage and overlap contribution points are refined by including and excluding viewpoints. Visibility analysis is categorized into single-viewpoint and multi-viewpoint analysis, depending on the number of viewpoints examined.

**Single Viewpoint Analysis Method**

Single viewpoint analysis focuses on continually improving algorithms like R3, XDraw (Franklin et al., 1994), and reference plane methods (Wang et al., 1996), which often struggle to balance accuracy and efficiency. To address this, researchers have proposed the view tree technique. This involves reconstructing Digital Elevation Model (DEM) data (Wang et al., 2023) and utilizing projection viewpoint to build the Proximity-Direction-Level-Line (PDERL) (Wu et al., 2021) and XPDERL (Guan et al., 2022) coordinate systems. Overall, the development of single-view watershed analysis algorithms is relatively advanced.



**Multi-view Analysis Method**

Unlike single-viewpoint analysis, multi-viewpoint analysis requires determining the positions and number of different viewpoints to optimize resource utilization or achieve specific objectives. Recent multi-viewpoint problem-solving strategies broadly fall into two categories:

**Computational Approaches:** This category utilizes intelligent algorithms (Ma et al., 2023; Civicioglu & Besdok, 2024), Apache Spark's multi-level distributed technology (Dong & Zhang, 2023), and GPU parallel computing capabilities (Xiao et al., 2024) to conduct view analysis on multiple viewpoints based on terrain data.

**Feature-Based Selection:** This approach selects potential viewpoints from featured terrain points within terrain files. While peaks are commonly chosen as potential viewpoints (Rana, 2003), practical implementations necessitate alignment with specific application scenarios. For example, a study selecting sites for fire lookout towers considered elevation values, slope, and accessibility (Sakellariou et al., 2022).

### 6.3. Point of View Selection Method in Architectural Photography

This approach focuses on identifying optimal vantage points for architectural photography. To understand user preferences in this context, the viewpoints associated with various images were analyzed

(He et al., 2016). A novel Riemannian metric was introduced to quantify the dissimilarity between viewpoints, considering the viewpoint space as a Riemannian manifold with Matrix Lie Group properties. This metric subsequently enabled the effective use of K-medoids clustering to validate observed preferences for viewpoints.

### 6.4. Multipoint Field of View Analysis Method

Line-of-sight (LOS) analysis is a spatial analytic technique in Geographic Information Systems (GIS) used to determine visible target regions from one or more viewpoints, aiding spatial cognition studies (Llobera, 2003). A Graphics Processing Unit (GPU)-based method then computes a visibility index for the resulting multidirectional space. Initially, an algorithm, informed by the field of view, generates parameters to facilitate the identification and quantification of buildings. The algorithm's effectiveness in DEM-based LOS analysis can be enhanced by optimizing candidate LOS locations (Tabik et al., 2013) or selecting optimal viewpoints (Wang & Dou, 2020; Yu et al., 2016).
The methodologies defined in this method include (Figure 10):



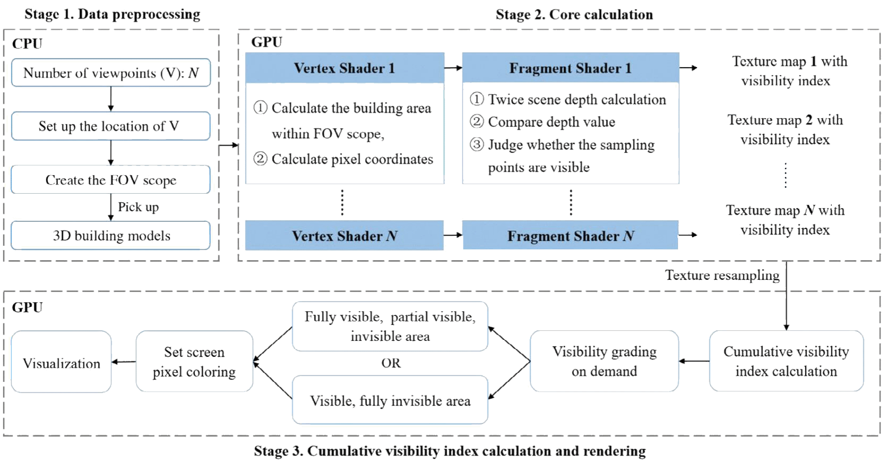


**Figure 10.** Flowchart of algorithms (Chen and Chen, 2021)

### 6.4.1. FOV-based scoping for view analysis

The horizontal radian angle of the line of sight (LOS), the vertical elevation angle of the LOS, and the maximum viewable distance from the observer are the three main components that determine a 3D field of vision (FOV). These parameters define a stereoscopic region that mimics a person's field of vision, with the observer at the origin. In Figure 11, the observer's horizontal field of view is shown in blue on the left, while the vertical field of view is shown in orange. On the right is the resulting field of view when three observers observe the same building from different positions.

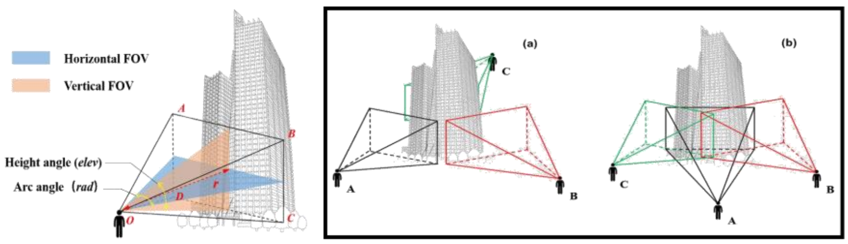


**Figure 11.** Scope based on FOV (left); 3 observers with a common area (right (a)), 3 observers without a common area (right (b)) (Adapted from (Chen and Chen, 2021)).

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### 6.4.2. An algorithm for parallel multipoint vision analysis based on shadow maps

This method employs GPU-based graph drawing, using the GPU's programmable pipeline to accelerate visualization and enable parallel processing. This technique has inspired various shadow rendering algorithms, which have been integrated into the viewpoint analysis methods outlined in (Chao et al., 2011; Zhao et al., 2013; Feng et al., 2015).

**Field of View Analysis Using Shadow Mapping:** Shadow mapping, introduced in (Williams, 1978), is a real-time technique that renders shadows by comparing data from two views. First, a depth map is generated by rendering the scene from the light source's viewpoint, where each pixel represents the closest surface depth (*D*). As shown in Figure 12, an object beneath the light source casts a shadow on the ground, illustrating this principle.

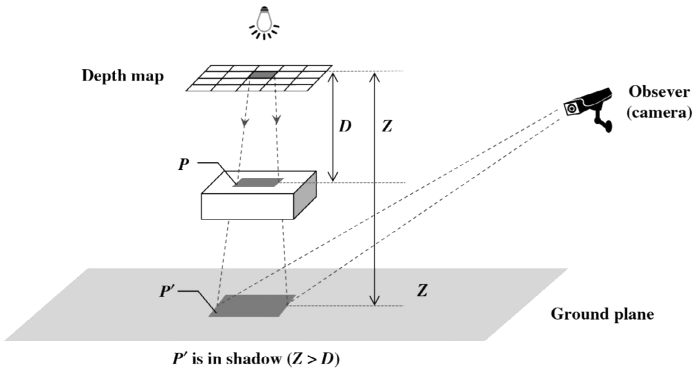


**Figure 12.** Algorithm for shadow maps (Williams, 1978).



**Depth Computation Aligned with FOV:** The algorithm begins by generating two depth maps of the target scene and comparing their depth values. It considers the viewpoint position, viewing direction, and target coverage to define the field of view (FOV). These parameters adjust the spotlight location, light direction, and depth range. Algorithm 2 (see (Chen and Chen, 2021)) combines these inputs to calculate scene depth.

**Cumulative Visibility Index:** As described in (Wheatley, 2022), a cumulative viewshed is created by merging multiple viewshed maps using basic map algebra. This technique supports the analysis of 3D building environments from multiple viewpoints.

### 6.5. Integrated Viewpoint Fusion and Selection Method for Best Object Recognition

This approach uses a reinforcement learning-based viewpoint selection method for active object recognition (Figure 13). The fusion strategy is based on the Densification Algorithm (Isard & Blake, 1998), with prior applications in viewpoint selection, image segmentation (Deinzer et al., 2003; Madsen & Christensen, 1997), and 3D reconstruction (Lehel et al., 1999).

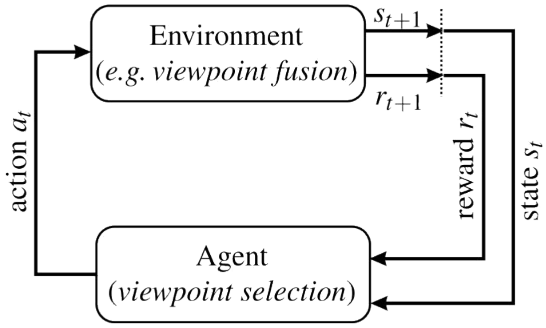


**Figure 13.** Reinforcement learning loop (Deinzer et al., 2006)

### 6.6. Viewpoint Selection Method with New Viewpoint-Based Selection Strategy

This method uses a deep metric learning approach to address viewpoint estimation. To try extract more discriminative and strong features, the viewpoint estimation problem has recently been tackled by convolutional neural networks, or CNNs (Su et al., 2015; Qi et al., 2016). According to recent studies, metric learning (Wang et al., 2017) appears to be a good fit for tasks involving viewpoint estimation and can also be used to learn spatial relationships.

#### 6.6.1. Creating a Dataset

CNN-based supervised learning models require large amounts of labeled images. To reduce data collection efforts, synthetic images are generated from CAD models, which are widely available in industrial settings and closely resemble real objects (Wang et al., 2016). Following prior studies, an object-centered view sphere with a fixed radius is used (Zhang et al., 2017).



#### 6.6.2. Method

**Viewpoint-based input selection strategy:** The distinction between views is used to identify positive and negative examples in a novel viewpoint-based triple input selection approach. Next, from one viewpoint, the Euclidean distance between the two samples was determined. Figure 14 presents the selection strategy in a more comprehensible manner**.**

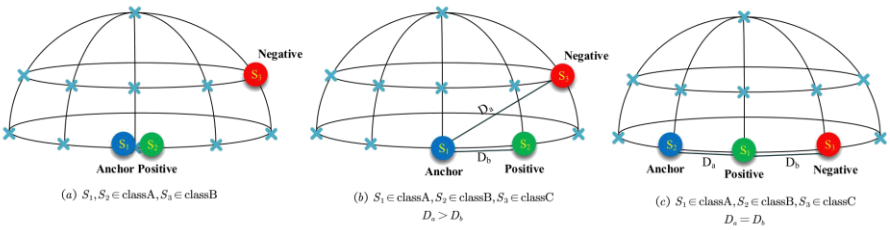


**Figure 14.** The illustration of the input selection strategy (Gu et al., 2019).

**Data preparation:** The data set for viewpoint estimation consists of five distinct workpieces, each photographed from multiple angles. These workpieces exhibit common industrial features such as uniform color, symmetry, and low texture. To capture varied conditions, each workpiece rotates around its central axis during imaging. Each image is systematically labeled with the corresponding viewpoint class based on the virtual camera's position.

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### 6.7. Imaging Network Design Method for UGV-Based 3D Building Renovation

This methodology introduces a novel photogrammetric approach for designing image networks in 3D building reconstruction (Hosseininaveh & Remondino, 2021). It involves two main steps: generating candidate viewpoints and selecting and grouping them. The first step includes identifying initial viewpoints, filtering them within an optimal range, and determining their orientation. The second step proposes four strategies—facade marking, center marking, hybrid, and combining center and facade marking.

**Materials and Methods**

The general building of the developed methodology consists of four main stages (Figure 15):

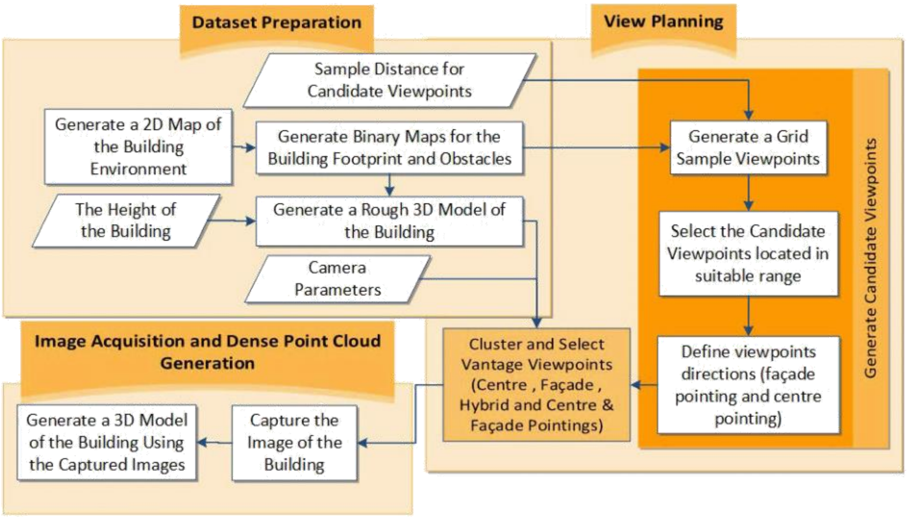


**Figure 15.** The proposed methodology for imaging network design for image-based 3D reconstruction of buildings (Hosseininaveh & Remondino, 2021)

Candidate viewpoints are generated through three steps: determining viewing direction, selecting candidate viewpoints, and creating a sample viewpoint grid.

**Viewpoint Selection:** Grid points corresponding to buildings or obstacles (black pixels) are removed. Views outside the camera's effective range are also excluded, based on photogrammetric constraints such as imaging scale ($D_{max}$ scale), resolution ($D_{max}$ Reso), depth of field ($D_{near}$ DOF), and field of view ($D_{max}/D_{min}$ FOV) (Hosseininaveh & Remondino, 2021).

**Clustering and Selecting Advantageous Viewpoints:** To select optimal views, a visibility matrix and viewpoint clustering are used. For each point on the rough 3D building model, a four-zone cone aligned with the normal surface is defined, following the method in (Ahmadabadian et al., 2017).

### 6.8. Efficient Viewpoint Selection Method for Urban Fabric Documentation

Participatory Texture Documentation (PTD) is a collaborative method for collecting urban texture data using mobile phone cameras. PTD consists of two phases, where important urban locations for texture capture are identified and viewpoints are distributed according to participants' preferences and constraints (Shirani-Mehr et al., 2009).

### 6.9. 3D Viewpoint Selection Method in Urban Planning

This method offers a theoretical and practical approach to automatically selecting optimal viewpoints to manage occlusion (Neuville et al., 2019). It introduces a Fly through Generation Algorithm (FGA) that computes effective camera paths for clear visualization of key 3D objects.

**Camera Settings**: The viewpoint management algorithm identifies optimal camera positions and orientations to observe target objects. Since it supports only parallel projection, the camera focal length is set to infinity. Although Camera 2 provides a wider field of view in Figure 16, the obstruction caused by the large building in the viewpoint projection (left) is greater than in the orthogonal projection (right).

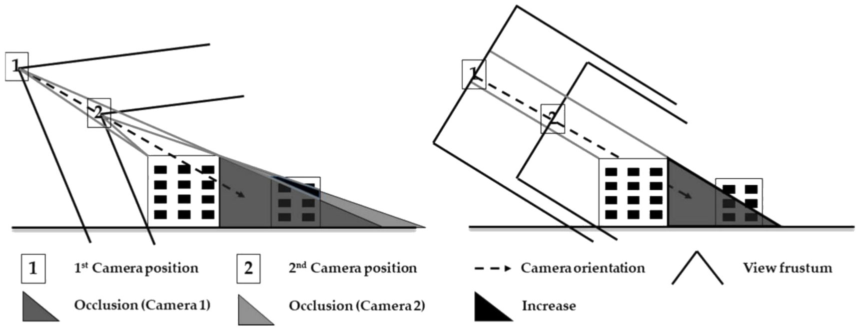


**Figure 16.** Viewpoint projection (left); parallel projection (right) (Neuville et al., 2019).



**Viewpoint Selection:** Several view descriptors have been developed to help choose optimal viewpoints, including view area, visible area ratio, surface area entropy, silhouette length and entropy, curvature entropy, and mesh saliency (Page et al., 2003; Polonsky et al., 2005).

**Method:** In the filtering phase, users first identify objects of interest within the visualization environment. Then, during mapping and rendering, the environment and objects are processed. Finally, the styles and objects are loaded into a 3D computational scene.

## DISCUSSION

This study has consolidated the various viewpoint selection techniques found across different disciplines in the literature into a systematic taxonomy in accordance with the PRISMA guidelines. The key discussion points identified in the context of the research questions (RQ) are as follows:

- **Systematization and Taxonomy (RQ1)**

The methods in the literature are divided into six main categories: geometric, aesthetic, visual features, semantic, deep learning, and architecture/urban model based (Table 2). This classification provides a comprehensive methodological framework that spans from micro-scale objects to macro-scale urban fabrics.

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**Table 2.** The classification and comparative analysis of viewpoint selection methods (source by authors)

| **CATEGORIZATION OF VIEWPOINT SELECTION METHODS** | | | |
|---|---|---|---|
| **Object-Oriented Selection Methods and Algorithms** | | | |
| **Categories** | **Method Name** | **Calculation Method** | **Tool / Program Used** |
| **Methods Based on Geometric Knowledge** | "General Position" Theory | Molecular visualization | curvature, silhouette, projection/ geometric area |
| **Aesthetic Evidence-Based Methods** | A Study of Viewpoint Based on Artistic Composition | Molecular visualization | silhouette |
| | Estimated area-based method (Low Level) | "80-ties" method | Geometric data, lines, planes |
| | Estimated area-based method (High Level) | Object predictability parameter | Geometric formulas / Mathematical algorithms |
| | Octree-based selection method | Visibility calculation parameter | Projected area of the surface |
| | **Methods Based on Information Entropy** | | |
| | - The Viewpoint Entropy Method | The entropy value of the projection areas | Open/closed stage area (3D) |
| | - Curvature Entropy Method | Curvature entropy | 3D model |
| | - Depth and Silhouette Entropy | - | Depth / silhouette |
| | - Other Entropy Methods | Wave transformation coefficients | 3D model |
| | A method based on Kullback-Leibler distances | Conditional probability matrix | Mathematical algorithms |
| **Methods Based on Visual Features** | Theory of Visual Perception (Visual attention model) | The linear center wrapping process | MATLAB, 3D models |
| | A visual perception model based on visual preferences | Global measurement function | Mathematical algorithms |
| | Curvature-based evaluation method | Visible surface characteristics | Histogram / Mathematical algorithms |
| | **Complexity-based assessment** | | |
| | - Histogram-based complexity | Patch painting | Histogram / Equation |
| | -Information theory-based complexity | Jensen-Shannon entropy | Probability transition matrix |
| | - Viewpoint Entropy (VE) | The relative area of projection surfaces on the sphere | Logarithms / Mathematical Equations |
| | Network Visibility-Based Selection | Mutual information) | Mathematical algorithms |
| | Vendor-Managed Inventory (VMI)-based selection | Polygon analysis | Mathematical algorithms |
| **Semantic-Based Methods** | Semantic network segmentation | Hybrid segmentation algorithm | Virtual 3D object models |
| | Choice of semantic viewpoint | The image-based annotation process | Mathematical scoring function |
| **Deep Learning Methods** | Viewpoint by region of interest (ROI) | Neural Gas Networks | 3D densification model |
| **Building-Oriented Selection Methods and Algorithms** | | | |
| **Categories** | **Method Name** | **Calculation Method** | **Tool / Program Used** |



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| | | | |
|---|---|---|---|
| Architectural and Urban Model-Based Methods | The optimal viewing angle for the visual impact of architectural heritage | Visual Impact Assessment (VIA) | ArcGIS software / C++ / GIS spatial analysis |
| | Skeleton-based view selection | Extraction of skeleton lines / Delaunay triangulation | ArcGIS software / C++ |
| | **Multi-viewpoint-based methods** | | |
| | - Single-Viewpoint Analysis | EPVPS algorithm | ArcGIS / Mathematical algorithms |
| | - Multi-Viewpoint Analysis | K-means algorithm | ArcGIS / Land data |
| | Choosing a Viewpoint in Architectural Photography | SfM (Building from Motion) / 3D point cloud model | Digital cameras / Smartphones / Image-based models |
| | Multi-point viewshed analysis | FOV-based coverage / GPU acceleration | 3D spatial buildings / Geographic information |
| | Integrated viewpoint fusion (for object recognition) | The reinforcement learning loop | Mathematical algorithms/ functions |
| | A new viewpoint-based entry selection strategy | CNN-based algorithms | Global coordinate system / Virtual camera / CAD |
| | **3D Building Reconstruction Using UGVs (Unmanned Ground Vehicles)** | | |
| | - Creating a sample viewpoint grid | Photogrammetric algorithm | Simulated UGV |
| | - Filtering by viewpoint within a specified range | The G-mapping algorithm | UAV / Python or C++ |
| | - Clustering and the selection of a favorable viewpoint | SLAM algorithm | ROS / Building map / 3D model |
| | Method for documenting the urban fabric | EPVPS algorithm | DEM (Digital Elevation Model) |
| | 3D Viewpoint Management in Urban Planning | FCA (Flythrough) / VMA (Management) algorithms | 3D Geo-visualization/ OpenGL API / Virtual Camera |



- **Methodological Differences and Areas of Advantage (RQ2)**

Object-oriented approaches are advantageous for maximizing visual clarity and information transfer by analyzing the geometric and semantic properties of individual objects. Building-oriented approaches, on the other hand, stand out for their ability to conduct spatial visibility assessments in complex urban scenarios by integrating GIS and user movement models.

In terms of accuracy and computational cost, while geometric and entropy-based methods are precise in identifying the mathematically “optimal” point, they can yield misleading results in buildings with high symmetry. In contrast, deep learning (CNN) models offer high adaptability and accuracy; however, they require large datasets and intensive GPU support.

- **Current Technological Approaches (RQ3)**

Today, CNN-based adaptive strategies in object analysis, and the EPVPS algorithm combined with GPU-accelerated real-time visibility

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analysis at the urban scale, are the modern approaches that yield the most effective results.

## CONCLUSIONS AND RECOMMENDATIONS

This study, which presents a systematic synthesis of 38 foundational works spanning the years 1988 to 2025, has resulted in the development of an analytical framework that highlights evolution, methodological trends, and scales of application of viewpoint selection techniques. This framework underscores the technological, temporal, conceptual, and methodological changes within the field.

### 1. Temporal Trends and Technological Transformation

Viewpoint selection methods have gone through three main phases over the past 35 years:

- **Geometric Foundations (1988–2000):** His early works focused on orthogonal projections and purely mathematical criteria such as the "least distorted surface." This period is characterized by limited computational power, yet it saw the introduction of fundamental optimization formulas.
- **Information Theory and Visual Perception (2001–2013):** With the introduction of concepts such as Shannon entropy and "Viewpoint Entropy" (Vázquez), the "amount of information" provided by an object has become the primary criterion. During this period, "saliency" models that mimic the human visual system were also developed.
- **Deep Learning and Large-Scale Analyses (2014–2025):** With methods such as CNN models and GPU-accelerated real-time urban visibility analyses, approaches have evolved from static analysis to dynamic and adaptive systems.

### 2. Comparative Analysis of Methods (Feasibility and Computational Cost)

The methods examined are summarized in Table 3 in terms of their scope of application and efficiency.

**Tablo 3.** A comparative summary of the methods examined in terms of their scope of application, computational cost, and analytical focus (sourced by authors)

| Category | Analysis Scale | Main Advantage | Limitations / Computational Cost |
|---|---|---|---|
| **Geometry & Entropy** | Micro (Object) | Mathematical precision, universal applicability | Misleading results in symmetric buildings, high computational power requirements |
| **Visual Perception & Semantics** | Micro-Meso | Human-centered aesthetic values, interpretation | Subjectivity based on user preferences, the need for labeled data |
| **Deep Learning (CNN)** | Flexible (Hybrid) | Adaptive learning, high accuracy | Very large training datasets and GPU dependency |
| **Architecture & Urban Planning (GIS/GPU)** | Macro (Architecture/City) | Real-time analysis, spatial efficiency | Sensitivity to data quality (DEM/CAD), complex algorithmic intrabuilding |

The comparative analysis yielded the following results:

- **Accuracy and Precision:** Geometric and entropy-based methods are effective at finding the mathematically "optimal" point, but they may lose accuracy in highly symmetric buildings. Deep learning methods, on the other hand, offer much higher adaptability and accuracy depending on the training data.
- **Computational Cost:** While traditional geometric methods can run on low CPU power, modern urban analyses (GIS-based) and deep learning models require intensive GPU support and large datasets.
- **Application Scale:** While object-oriented methods are effective in micro-scale contexts such as museum and product design, building-oriented methods (GIS, SfM) are applied at macro-scale contexts such as urban landscapes and architectural heritage.

**Table 4.** Summary table: Comparative synthesis of methods (sourced by authors)

| Category | Analysis Focus | Basic Tools | Application Advantage |
|---|---|---|---|
| **Object-Oriented** | Geometry, Entropy, Aesthetics | MATLAB, 3D Models | Museum exhibitions, product design |
| **Building-Oriented** | GIS, GPU Analysis, Urban Data | ArcGIS, C++, Python | Urban planning, architectural heritage |
| **Modern Approaches** | Deep Learning (CNN), Semantics | GPU, Neural Networks | Adaptive and intelligent selection systems |



The distribution of the 38 core studies examined shows that object-oriented methods (geometric, entropy, semantic) have a longer history in the literature, while building-oriented methods have gained momentum over the past decade thanks to technological advancements (GIS, GPU) (Table 4). Based on these findings, the methodological framework of the study, the proposed technological action plan, and its contribution to the literature are outlined below:

- **Methodological Bridge:** While object-oriented methods answer the question "what should be looked at" through aesthetics and information density, building-oriented methods answer the question "from where one should look" through spatial visibility and user movement.
- **Action Plan:** In hybrid fields such as smart cities and digital museology, combining the adaptive capabilities of deep learning with the spatial precision of GIS emerges as the most effective strategy.
- **Future Perspective:** Rather than a statistical synthesis (meta-analysis), this study presents a qualitative and taxonomic synthesis of literature. It is recommended that future studies quantitatively compare the computation times and user satisfaction rates of these methods.

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## Resume

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