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# Point clouds as an efficient multiscale layered spatial representation

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**Abstract**

*3D point clouds describe urban shape at different scales, precisions and resolutions depending on the underlying sensors and acquisition methodology. These factors influence the quality of the data, as well as its representativity. In this paper, we propose a multi-scale workflow to obtain a better description of the captured environment through a multi-scale representative point cloud, presenting an unlimited depth and multisensory data fusion. Our method is shown over a "smart point cloud" data structure and based on data fusion principles retaining higher description and precision on overlapping areas. The concept is illustrated through a use case on the castle of Jehay (Belgium), where aerial LiDAR data, terrestrial laser scanner point cloud and photogrammetry-based reconstruction are combined to obtain a multi-scale data structure.*

Categories and Subject Descriptors (according to ACM CCS): I.2.10 [Artificial Intelligence]: Vision and Scene Understanding—Intensity, color, photometry, and thresholding; Representations, data structures, and transforms

## 1. Introduction

Due to the rapid development of surveying and reality capture technologies, the acquisition of point clouds continues to become easier and faster while incurring lower costs. Through a wide variety of sensors and acquisition methodologies, we generate point clouds at different scales, with different attributes, precisions and resolutions.

The potential of an unlimited depth regarding the nature of point primitives is of great interest when dealing with multiple heterogenic datasets. Considering applications depicted in [WJH*2015] or for land management, construction planning, visualization, navigation, simulation and facility management, point cloud measurements permit to overcome outdated interpolated content when the 3D point cloud partially changes [RD2013]. However, due to urban variations over time and land mapping specific needs, we often dispose of different datasets describing the same region with different levels of abstraction. Combining efficiently this information with multi-scale acquisition techniques is interesting because it provides a complementarity visible through smoother and finer description of our world. But the heterogeneity becomes a challenge for multi-scale structuration and analysis. Combining efficiently this information is often complicated due to fluctuations in resolution, precision, semantics and temporality that create unbalanced and confused representations.

In this paper, we address challenges regarding point cloud data fusion of multi-scale datasets for pertinent multi-level analysis and visualisation of urban data. In this context, domain knowledge has a major influence as it adapts which information is available and/or necessary for the end user. Therefore, to get exhaustive representations, knowledge extracted from a reliable device expertise as defined in [PNH*2016] is mandatory to provide efficiency and scalability over available multisensory information. The combination of semantic components that can be extracted thus provide a base for data visualisation [FWG2002] to address visual components that elegantly represent the analytical results.

Firstly, we will establish a workflow combining device, domain and analytic expertise to process multi-resolution point clouds from multisensory systems to efficiently aggregate available information. Then, we will discuss the suitability to multi-scale data mining of a previously defined smart point cloud (SPC) data structure [PNH*2016]: a knowledge-based structure built on a semantical level of detail (LoD). Finally, we will verify the applicability through a case study on the castle of Jehay in Belgium, by fusing aerial LiDAR data, orthophotos, terrestrial laser scanner (TLS) point clouds and photogrammetry-based reconstructions to obtain a multi-scale point cloud structure. Adaptive representation and class-based rendering will also be discussed as being an efficient way to visualise the data.

## 2. Combining multi-resolution and multisensory systems

The work described in [Kle2004] reviews extensively data fusion algorithms defined by the U.S department of Defense Joint Directors of Laboratories Data Fusion Subpanel as *"a multilevel, multifaceted process dealing with automatic detection, association, correlation, estimation and combination of data and information from single and multiple sources to achieve refined position and identify estimates, and complete and timely assessments of situations and threats and their significance"*. Indeed, the combination of different sensors generating different yet complementary signature provides relevant information without the limitations of a single use and creates a multisensory system [Pet2009].

The sensor's choice mainly depends on the context, the precision and the resolution that a specific application domain demands. To





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describe accurately a scene composed of scattered observations, high fidelity scene descriptors from sensors are essential. The process to identify interesting features within the signal is the foundation for the creation of multi-scale ensembles from different datasets. Indeed, selecting accurate and complementary attributes that are available from information sources permits to overcome limits arising from a small set of features.

A pre-processing step is necessary to obtain a highly representative signal of the value measured, as defined in [OGW*2013]. Indeed, to avoid external influential sources that degrade the information, this step demands adapted techniques to minimize errors including noise, outliers and misalignment. Filtering the data highly depends on device expertise, as aerial LiDAR data characteristics differ from terrestrial laser scanner (TLS) data and photogrammetry-based point clouds in terms of geometric consistency, attached attributes, resolution, precision and relayed information.

The knowledge around the acquisition methodology is an important information as missing/erroneous data, misadjusted density, clutter and occlusion are problems that can arise from an improper or impossible capture configuration on the scene [DG2015], resulting in a loss of transmitted information or data quality. Combining different sensors with diverse acquisition methodologies allows to overcome this challenge and provide a better description of the captured subject through:

- Higher quality features, for example better colour transcription, better precision, accurate semantic description;
- Specific and unique attribute transfer;
- Resolution and scale adaptation, sampling or homogenizing.

The knowledge extracted from a device expertise, analytical expertise or a domain formalisation constitute the fundamental information repository on which a multi-scale data structure is constructed. Therefore, device and analytical expertise constitute two knowledge sources for fusing multisensory point cloud data.

Using these to complete domain knowledge demands the creation of a workflow to define the complementarity, the importance of each sensor's attribute and a priority processing when similar geometrical features overlap (i.e. which point cloud or attribute is considered and processed first).

We first introduce the geometrical overlap as a threshold under which two point cloud entities, noted $A = (a_1, a_2, \ldots, a_n)$ and $B = (b_1, b_2, \ldots, b_n)$ are considered overlapping:

$$\sqrt{\frac{\sum_{i=1}^{n}(a_i - b_i)^2}{n}} \leq T_g \qquad (1)$$

Where $T_g$ is the threshold defined in regard to the domain knowledge (user-centered), $a_i$ is a point $i$ from the point cloud $A$, and $b_i$ the nearest point $i$ from the point cloud $B$.

To optimize calculations and to determine in a global context overlapping areas, we first determine the bounding box parameters of unstructured point clouds of the finer resolution, first segmented via a connected components approach [ST88] to keep local comparisons pertinent. When the dataset resolution differs from the sampling resolution (e.g. variable inner density due to different set-up for TLS, different geometry and orientation of captured environment surfaces) point cloud rough densities are calculated to determine which point cloud has the higher density therefore finer resolution (i.e. points / m$^3$). The calculation considers all k-nearest neighbours (k-nn) per defined search sphere volume for each point, and average each result by the total number of points:

$$\forall\, a_i \in A, d_{a_i} = \frac{N_{a_i}}{\frac{4}{3}\pi R^3} \; and \; D_A = \frac{\sum_{i=1}^{n} d_i}{n} \qquad (2)$$

Where $N_{ai}$ is the number of neighbours of the point $a_i$ of the point cloud $A$, $R$ is the search sphere radius, $D_A$ is the rough density estimate of the point cloud $A$.

Then, we select each point of other datasets within the bounding box, and the threshold validation (eq. (1)) is conducted by a k-nn search combined with Euclidean distances calculation to define geometrical point cloud attribute similarity. However, to avoid comparing point cloud from sensors too different in terms of precision and resolution (e.g. a 1 m with a 1 mm point cloud where precisions are out of range) that would provide wrong descriptors, we establish a normalized indicator that should not exceed domain knowledge defined specification limit $T_r$:

$$\forall\, (D_A, D_B) \in \mathbb{R} \mid D_A \geq D_B, \qquad I = \frac{D_A}{D_B}, I \leq T_r \qquad (3)$$

Where $D_A$ is the resolution (average density) of the point cloud a, $D_B$ is the resolution (average density) of the point cloud B.

When combining different point clouds, their geometry and attributes in overlapping areas is then properly addressed. The complementary information needs to be combined from the different available sources if relevant, keeping the most precise geometry as structure. Avoiding heterogeneous precisions is essential, leading to point deletion rather than point caching and fusing. To fuse complementary attributes from point clouds, we establish the following workflow:

1. Selecting all points that lie under the geometrical similarity threshold of the two overlapping entities (eq. (1)) if eq. (3) is validated;
2. Defining a quality indicator for each coordinate and attribute regarding available knowledge information (precision per point, colour fidelity, specific sensor's attribute, …), and identifying a priority level based on the extracted quality indicator;
3. Transferring to the most geometrically accurate point cloud new relevant attributes (if not already existing) following the priority list, based on a k-nn attribute transfer;
4. Replacing attributes if their priority level is higher (higher quality descriptor);
5. Deletion of points of lower representativity inside the overlapping area extended by a resolution-based buffer (replacing in eq. (1) $T_g$ by $T_g$+$D$).

The obtained point cloud through this fusion pipeline is thus more representative of the underlying information, both geometrical and semantical. Once every point cloud has been processed in a pyramidal way regarding resolution, we obtain a multi-scale point cloud from multiple capture conditions.

Data visualization is important to explore the data, to get some idea of what it contains, and therefore, to develop some intuitions on how to go about solving a problem from that data, determining what features are important and what kind of data are involved. In the context of point clouds, semantics and domain can highly influence the type of rendering used to directly transmit the correct information in a correct way to the end user, as featured in [RD2010]. Addressing multi-scale representation by combining methodology, signature information and resolution is convenient to create pertinent representations with a potential unlimited depth (points are no dimension primitives). Therefore, adapting point-based representation [MJP*2016] through attributes, class information and acquisition methodology allows powerful visualisation possibilities for multi-scale urban data. The use of the richness of surface geometry through local descriptors extracted through a device expertise provides a good solution for multi-scale adaptation. They often rely on region growing algorithms based on a smoothness constraint regarding edge-based, top-down and bottom-up surface segmentation or scan-line as stated in [RVV2006] which is mainly determined through the similarity criterion conditioned by the initial threshold. Normals are powerful local or global descriptors used as a base of region growing, but their representativity heavily relies on neighbourhood selection encapsulating 3D points from a search definition commonly spherical, cylindrical, or k-nearest points in 2D or 3D [WJH*2015]. Results implicitly depend on the size adaptation, therefore scale of the search that will generate a feature descriptor either global or local. We propose to use these second order descriptors to adapt point orientation as well as the point size display regarding the point cloud density. Yet, the multi-scale data creation relies on a structure that can efficiently answer both analytical and visualisation needs.

## 3. Discussions on data organisation

Large volume and high resolution of point cloud data make it suitable for LoD management and rendering. The data model that determines the logical structure of a database will determine in which manner the data can be stored, organized, and manipulated. While file-based are common point cloud storing systems managed through hierarchical-like database models, sharing, compatibility, query efficiency and data retrieval are the main limitations in these models. [OGW*2013] reviewed extensively existing large point cloud data structures including attribute and geometrical information organization. They rightfully state that the secondary storage access limits data-intensive tasks, that could be solved through streaming algorithms to keep small parts in-memory. However this implies pre-sorting and structuring a priori the data. In their discussion, they propose to separate coordinates from features in the DBMS to permit efficient attribute updates as well as georeferencing and spatial reorganization.

This approach is particularly suited when combining point cloud from different sensors with varying densities and attributes (Figure 1). While our proposed multi-scale data fusion workflow can be carried onto any point cloud data structure, the smart point cloud concept [PNH*2016] provides additional mining and visualisation possibilities due to the integration of knowledge in the pipeline and intelligence linked to the point cloud.

A multi-scale point cloud data structure for multi-scale merged datasets must retain:

- Unique information to each sensor and available domain knowledge (semantic intelligence);
- A 3D point cloud geometry description;
- Per-point representative attributes.

To make this data structure efficient, search queries (both for analysis and visualisation) and data retrievals must be performed over a balanced structure. The SPC specificity combining a spatially indexed structure efficient for spatial queries with a LoD schema that retain relationship and semantics for other attribute queries is particularly interesting and constitute the base structure. The effective smart data structure is illustrated in Figure 1 but its definition extends the scope of the article and is presented in [PNH*2016]. Such a scale adaptive structure can also handle feature descriptors which can play over sub-space or global scales.

Retaining relations and organizing via a hierarchical topological LoD based on semantics define a domain-based structural organization which include classification of detected objects within the point cloud. LoD rendering techniques for multi-scale point cloud without semantic intelligence build on [SW2015] implementation, by extending it using device and analytical extracted knowledge (k-nn normal computation for point orientation and density calculation for LoD size adaptation). Normals permit to orient point drew on the screen as a density-based (eq. (2)) sized screen-aligned square (or disk) based on the local node level (in a LoD data structure) and the distance to the viewpoint. Point-based primitive rendering using OpenGL has been extensively studied [SP2004] and used [MJP*2016] and provides an efficient rendering framework.

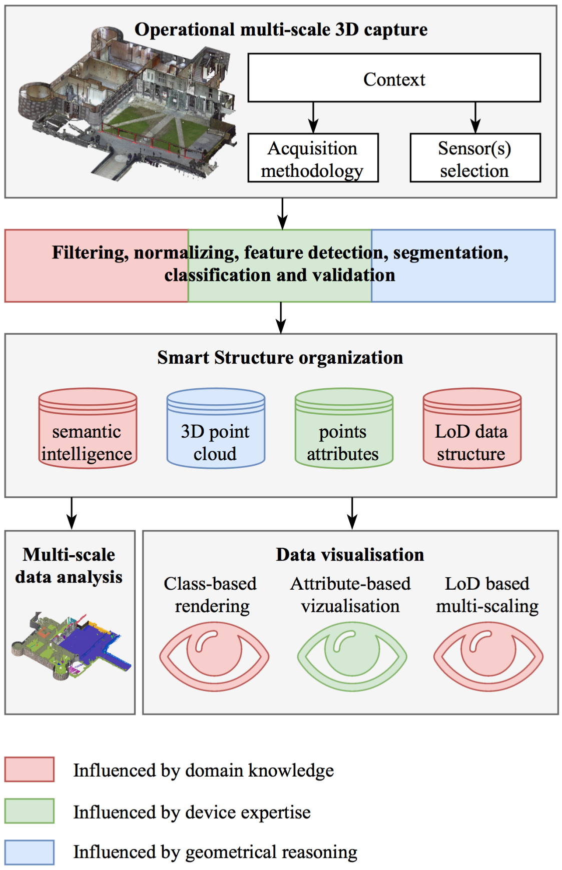


**Figure 1:** *Workflow from Smart Point Cloud structuration to multi-scale adaptation*

In the context of point clouds, semantics and domain can highly influence the type of rendering used in order to directly transmit the correct information to the end user. The use of points as rendering primitives [SP2004] allows a more general approach that outperform triangle based rendering for complex natural shapes and different captured scales both in speed and quality. It avoids interpolation or approximating a set of unorganized points benefiting of a theoretical unlimited depth in the LoD. However, triangulated approaches are nowadays still largely used for their better integration and available implementations. Based on LoD concepts aggregating points regarding attributes, [RD2010] define a new class-attached point cloud out of core rendering system by storing points in a layered multi-resolution kd-tree. Point cloud object class information a priori computed allows different rendering techniques such as silhouette rendering and splatting depending on the visual information that needs to be communicated. [RD2013] present a system architecture to manage massive point cloud, including database integration, interactive rendering and visualisation through class-based rendering. In the paper, the authors clearly identify important advantages of point clouds over models: they are LoD adaptive and allow fast update without the need to remodel, or re-extract information. Therefore, point cloud can be much less effort for specific task of integration and comparison. The concept of vario-scale [HMS*2016] providing near-continuous capabilities is interesting and should be studied for an alternative to the “Block effect” of discrete LoD data structure.

## 4. Case study: Jehay’s castle

The integration of multiresolution data from different LiDAR (active) and CMOS (passive) sensors is a first step toward the virtualisation and context integration of the castle of Jehay. The data was captured at different times and from different sensors:

- In 2013, an aerial LiDAR capture campaign was conducted using a Riegl Litemapper 6800i LiDAR sensor with a regular pulse repetition rate of 150 kHz to obtain between 0.78 pt/m² (at 1500 m) and 0.96 pt/m² (at 1200 m²) in the final point cloud (APC, Figure 7). The interest region covers 84 km².
- In 2016, we surveyed using the ground terrestrial laser scanner Trimble TX5, a phase-based scanner to obtain a 3-mm average resolution point cloud (LPC) of a part of the park, indoor and facades (Figure 3) of the castle of Jehay. The interest region covers 0.014 km².
- In 2016, we made a terrestrial photogrammetric reconstruction of the facade of the castle of Jehay based on 146 photos shot in RAW, at a resolution of *4896x3672* using a consumer grade camera (SONY DSC-HX200V). The obtained point cloud (PPC) has a final resolution of 2 mm (Figure 2).

The registration of the different entities was made using ground control points (GCPs) and different target registered using the total station Leica TCRP1200, in the global system ETRS89 Belgian Lambert 2008. Misalignment between entities was controlled by comparing Iterative Closest Point (ICP) adjustments with global position via GCPs.

To merge these datasets a pre-processing step of the raw data is necessary (as defined in part 2) to obtain higher representativity through scene descriptors. Mostly, clutter from reflections and attenuation correction takes place, while no interpolation at this stage is mandatory. Filtering terrestrial laser scan data based on the range, the capturing angle and the signal intensity was also performed to obtain a unified and homogeneous point cloud. We can then compare the different datasets to prioritise and classify based on the resolution (eq. (2))) and precision of the datasets:

| Type | Number of points | Average resolution |
|---|---|---|
| PPC | 862 million | 2 mm |
| LPC | 437 million | 3 mm |
| APC | 287 million | 1 m |

Then, over the smallest entity with the finer resolution (PPC), we calculate the bounding-box and select all points from different datasets that fall within.

**Figure 2:** *3D coloured point cloud of the photogrammetric reconstruction (PPC)*

| Bounding-box parameters | |
|---|---|
| Length | 41.937m |
| Width | 41.293m |
| Height | 32.744m |
| Volume | 56703 m$^3$ |
| Center | [717593.600; 641169.200; 185.898] |

Inside the bounding-box, 1719 points from the APC point cloud are selected, and 264103895 points from the LPC. At this stage, in order to obtain efficient comparison regarding eq. (3), we ignore the APC dataset where $I = 500$ (density 500 times lower than PPC, calculated from eq. (2)).

Then we conduct a similarity analysis regarding part 1 to select all points of the LPC that fall under the similarity threshold $Tg$ (eq. (1)) defined regarding the reconstruction contextual specification as obtained from device expertise (max deviation between LPC and PPC): 10 cm. 65849052 points answer this criterion with the LPC entity, which covers only the exterior facade.

**Figure 3:** *3D reflectance only facade point cloud from the Trimble TX5 laserscanner (LPC)*

All points belonging to indoor and farther than 10 cm from PPC are automatically excluded. We noticed that this method also permits to automatically clean noise due to windows and other scan artefacts. The calculated Gauss standard deviation is 0.028 m and we note that the biggest differences between PPC and LPC point clouds happen over lower overlapping photo reconstructed elements.

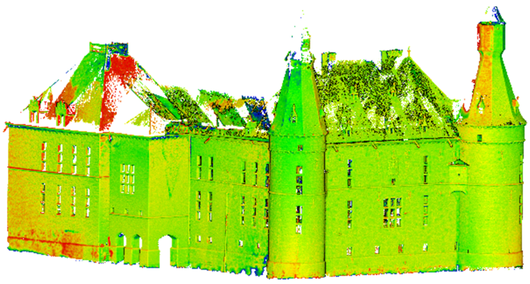

**Figure 4:** *Color-coded distances between LPC and PPC point cloud*

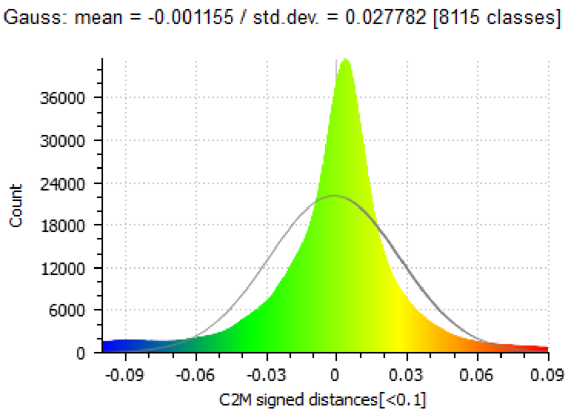


**Figure 5:** *Distances histogram between PPC and LPC point clouds in meters*

The laser scan data has no colour attributes over these points, therefore combining signatures provides efficient new descriptors for the point cloud. In order to accurately transfer attributes, we first select homogeneous zones where a threshold *Tg* of 2 cm (contextually defined by the applicant) is validated, in order to retain a precise colour overlay. Finally, the colour is transferred to the most precise point cloud (LPC) via k-nn transfer, to obtain 44039955 coloured points, representing 67% colorization of the initial LPC facade.

**Figure 6:** *Point cloud from combining photogrammetric reconstruction and lasergrammetry acquisition*

This process is repeated for every overlapping area, to finally obtain a smooth multi-scale combination of the different datasets.

**Figure 7:** *Colored LiDAR point cloud by combining orthophotos with LiDAR signal over zone of interest*

**Figure 8:** *PPC,LPC, APC point clouds combined without resolution adaptation*

**Figure 9:** *Zoom in-view from the parc combining all datasets with resolution-adapted LPC point cloud*

Finally, in order to obtain a fluent navigation and visualisation over all scales from a terrestrial and aerial point of view, we adapt the rendering based on extracted analytical knowledge: points are oriented regarding to computed normals (estimated via k-nn search) and their screen size is representative of the local resolution (density) of the point cloud. This adaptive rendering allows to avoid blank space that our eyes cannot fully interpret, without interpolating and creating uncertain and time consuming surfaces. In Figure 10, we compare over a zone of interest (the park of Jehay) the adaptive rendering concerning the APC point cloud.

**Figure 10:** *From left to right, 10 cm adapted point size, 80 cm adapted point size, 120 cm adapted point size*

When adaptive rendering is combined with class-based rendering, semantic information can be visually transmitted to the end user and easier to grasp.

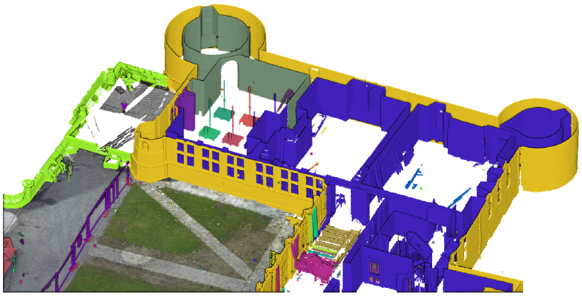

**Figure 11:** *Class-based rendering after initial SPC segmentation*

In Figure 11, after initial segmentation of the point cloud and classification regarding Level 1 SPC as defined in [PNH*2016], we obtain a user-oriented class-based rendering.

## 5. Conclusions

Fusing data from both active and passive sensors provide additional information that relays through higher representative feature for contextual structuration and visualisation. This article showed the benefits of combining different features from these sensors while addressing specific challenges being registration, resolution adaptation, and attribute fusion to obtain a multiscale representation from urban scale to building scale. The case study of the castle of Jehay illustrated the concept and applied the workflow to obtain a highly representative multi-scale point cloud combining heterogeneous datasets with varying resolution from LiDAR, photogrammetric reconstruction and terrestrial laser scanner.

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