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Registration for Urban Modeling Based on Linear and Planar Features

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Abstract—The production of a Building Information Model (BIM) from an existing asset is currently expensive and needs automation of the registration of the different acquisition data, including the registration of indoor and outdoor data. This kind of registration is considered a challenging problem, especially when both data sets are acquired separately and use different types of sensors. Besides, comparing a BIM to as-built data is an important factor to perform building progress monitoring and quality control. To carry out this comparison, the data sets must be registered. In order to solve both registration problems, we introduce two efficient algorithms. The first offers a potential solution for indoor/outdoor registration based on heterogeneous features (openings and planes). The second is based on linear features and proposes a potential solution for LiDAR data/BIM model registration. The common point between the approaches consists in the definition of a global robust distance between two segment sets and the minimization of this distance based on the RANSAC paradigm, finding the rigid geometric transformation that is the most consistent with all the information in the data sets.

Index Terms—Planar region, 3D segments, Openings, RANSAC, BIM, Clustering, Registration, Global robust distance.

I. INTRODUCTION

The indoor and outdoor modeling of buildings from images and dense point clouds is an important issue in building life cycle management. The objective is to achieve a complete, geometrically accurate, semantically annotated but nonetheless lean 3D CAD representation of buildings and objects they contain in the form of a Building Information Model (BIM). BIM helps to manage buildings in all their life cycle (renovation, simulation, deconstruction). The first challenge is to accommodate heterogeneous data as full building modeling calls for data acquisition inside and outside the building. BIM production is currently very expensive and needs automation of the registration of the different types of acquisition data. The indoor/outdoor registration is considered as a challenging problem for this kind of production, especially when both data sets are acquired separately and use different types of sensors. Comparing a BIM to as-built data of the same building is also necessary to perform building progress monitoring and quality control. To carry out this comparison, both data sets must be in the same coordinate system and a registration step is necessary.

A. State of the art

1) *Indoor/outdoor registration*: The registration of indoor and outdoor scans is a challenging problem for building modeling. The lack of overlap between indoor and outdoor data is the most prominent obstacle, especially when both data sets are acquired separately and use different types of sensors. Though indoor/outdoor registration is a very difficult problem, there have been several attempts to solve it. State-of-the-art approaches have used two types of features separately or together: geometric and semantic features. The key points are special points that hold important information about the global structure of the point cloud. A key point integration with the ICP algorithm (Iterative Closest Point) has been proposed in [6] to register the point clouds. When overlap between indoor and outdoor scans is low, additional information provided by the data can help the registration algorithm. The authors of [17] have extracted line segments of windows to automatically align indoor and outdoor models. To register scans with a small overlap in arbitrary initial poses, the authors of [5] have proposed a plane/line-based descriptor dedicated to establishing structure-level correspondences between point clouds. A planar polygon detection and matching method has been introduced in [1] to address the challenging problem of indoor/outdoor registration. The choice of planar polygons as appropriate attributes is grounded on the fact that they have a spatial extent limited to the areas where they have supporting points in the input data, so they form a good abstraction of the LiDAR scans. A semantic feature-matching method has been proposed in [7] to align an indoor and an outdoor point cloud. The basic idea is to include both the objects' semantic information and spatial distribution pattern by designing a semantic geometric descriptor (SGD). An efficient method for merging disconnected indoor and outdoor models of the same building into a single 3D model has been proposed in [16]. This method took semantic information (window information) into consideration to obtain candidate matches from which an alignment hypothesis can be computed.

2) *LIDAR data/BIM model registration*: Building Information Modeling (BIM) is seen as an important technology for building life cycle management. It plays a fundamental role in several stages, such as building progress monitoring and

quality control. The progress monitoring task is based on the comparison between the as-built (the scan model of the building) and the BIM. To carry out this comparison, both data sets must be in the same coordinate system, hence a registration step is necessary. A patch-based co-registration with several static laser scans and BIM has been introduced in [8]. The main objective of this approach is to avoid the need for ground control points. An efficient method to solve the registration problem for scan/BIM has been proposed in [9]. The proposed method uses the corner points of the building structure and finds their congruent pairs to compute the optimum transformation. The authors of [10] have studied an automated registration method that aligns the as-built point cloud of a building to its as-planned model using its planar features. The basic idea is to measure the correspondence between the plane segments through a matching cost algorithm. This matching step leads to the determination of the transformation parameters to correctly register the as-built point cloud to its as-planned model. In order to co-register videogrammetric point clouds with BIM, the authors of [18] have introduced an improved matching algorithm to match 3d lines (from images) and 3d planes (from BIM).

B. Overview and contributions

The work carried out has confirmed that the environment and the type of data drive the choice of the registration algorithm [12]. So, the objective of this work is to explore the fundamental properties of the data and the environment in order to propose potential solutions for two challenging registration problems: indoor/outdoor registration and BIM model/LiDAR data registration. The man-made environments are rich in planar and linear features because they are mostly composed of elementary geometric primitives (planar polygons, openings, ...) delimited by 3D segments. Given this property, we have chosen to introduce new registration algorithms based on the minimization of global robust distance defined between two segment sets.

Our first methodological contribution is a new global distance between two 3D segment sets. Its first quality is that it is robust to segments present in one set but having no counterpart in the other set, yielding a nominal penalty for such a case. Moreover, it takes into account the fact that a long segment in one set may be detected as several shorter segments in the other set by using a notion of overlap between 3D segments. Our proposition for registration is to minimize this global distance using a guided RANSAC paradigm. This is implemented in our two demonstrated applications: the registration of indoor and outdoor LiDAR scans and the registration of indoor LiDAR scan to a BIM.

In Section II, we detail the robust global distance between 3D segment sets. Its usage for indoor/outdoor registration is explained in Section III and in Section IV for LiDAR data/BIM registration. Some experimental evaluation is presented in Section V and Section VI concludes the article.

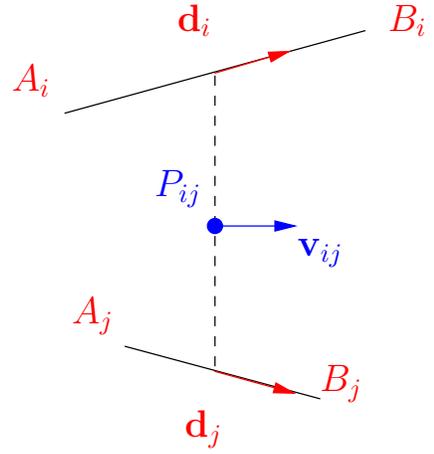


Fig. 1: Bisector line associated to two 3D segments $[A_i B_i]$ and $[A_j B_j]$. It goes through the barycenter P_{ij} of the segment endpoints and has direction \mathbf{v}_{ij} .

II. GLOBAL ROBUST DISTANCE BETWEEN TWO SEGMENT SETS

Inspired by [11], we propose to define a robust distance between two 3D line segment sets in a way that minimizing this distance will favor significant overlaps between segments and small distances over these overlaps while being robust to outliers, which is to be expected as it is possible that a segment extracted from one data set will have no counterpart in the other. We start first by defining the distance between two segments $s_i = [A_i B_i]$ and $s_j = [A_j B_j]$ by projecting orthogonally s_i and s_j on their bisector line $B(s_i, s_j)$, resulting in segments s'_i and s'_j . $B(s_i, s_j)$ is the line going through P_{ij} , the barycenter of the 4 endpoints (see Figure 1).

The direction of the bisector line is $\mathbf{v}_{ij} = (\mathbf{d}_i + \mathbf{d}_j)/2$. The projection $p_{ij}(P)$ on the bisector line of a point P is defined as

$$p_{ij}(P) = P_{ij} + ((P - P_{ij}) \cdot \mathbf{v}_{ij}) \mathbf{v}_{ij}, \quad (1)$$

whose abscissa is $c_{ij}(P) = (P - P_{ij}) \cdot \mathbf{v}_{ij}$. The projected segment s'_k is defined by its endpoints $[p_{ij}(A_k) p_{ij}(B_k)]$ and its length is

$$|s'_k| = |c_{ij}(A_k) - c_{ij}(B_k)|, \quad (2)$$

and the overlap length is

$$|s'_i \cap s'_j| = \min(\max(c_{ij}(A_i), c_{ij}(B_i)), \max(c_{ij}(A_j), c_{ij}(B_j))) - \max(\min(c_{ij}(A_i), c_{ij}(B_i)), \min(c_{ij}(A_j), c_{ij}(B_j)))) \quad (3)$$

The distance between the two segments is defined as

$$D(s_i, s_j) = \frac{1}{2} (D(G_i, s_j) + D(G_j, s_i)), \quad (4)$$

which involves the center points $G_k = (A_k + B_k)/2$, and the point-to-segment distance

$$D(G, [AB]) = \|G - p_{[AB]}(G)\|, \quad (5)$$

where the projection over the segment is

$$p_{[AB]}(G) = \begin{cases} A & \text{if } (G - A) \cdot (B - A) \leq 0 \\ B & \text{if } (G - B) \cdot (A - B) \leq 0 \\ A + \frac{(G-A) \cdot (B-A)}{\|B-A\|^2} (B - A) & \text{otherwise.} \end{cases} \quad (6)$$

This latter corresponds to a projection on the line joining A and B , then a clamping of this point to the segment $[AB]$. The distance between a segment s_1 and a set of segments S_2 is then defined as:

$$D_d(s_1, S_2) = d^2 - \sum_{s_2 \in S_2} \frac{|s_1' \cap s_2'|}{\min(|s_1'|, |s_2'|)} \max(0, d^2 - D(s_1, s_2)^2). \quad (7)$$

where parameter $d \in \mathbb{R}^+$ is a robustness parameter (all segments above this distance are considered unmatched and contribute equally to the distance). The first factor under the sum is a relative overlap of the 3D segments and is within the interval $[0, 1]$. Aggregating over all segments of S_1 , we can write our global robust distance between two sets of 3D segments:

$$D_d(S_1, S_2) = \sum_{s_i \in S_1} D_d(s_i, S_2). \quad (8)$$

Let us justify the distance (7). First, if all segments of S_2 are too far from s_i ($D(s_i, s_j) \geq d^2$), all terms under the sum vanish and a nominal cost d^2 is paid. It means that “unmatched” segments in S_2 all contribute the maximum d^2 . Second, if we have a segment s_j that covers s_i ($s_i' \subset s_j'$) the relative overlap is 1 and the associated cost is $D(s_i, s_j)^2$ provided it is smaller than d^2 . The parameter d represents the maximum distance for which two 3D segments are considered as partially matching and a meaningful value related to the precision of the scan can be selected.

III. INDOOR/OUTDOOR REGISTRATION

Openings are the most obvious common entity to link the inside and outside data. As such, they can help the registration of indoor and outdoor point clouds, so they must be automatically, accurately, and efficiently extracted. Therefore, in order to improve indoor/outdoor registration, we integrate the openings into our registration framework. The selection of opening correspondences is a crucial step for a successful registration because a bad choice can lead to a bad estimate of the optimal transformation. In our case, the features are two opening sets detected from indoor and outdoor scans. The openings are not characteristic enough to match them robustly independently. As an opening is defined by a rectangular shape composed of four segments, two of them horizontal and two vertical, and inspired by [3], we can write our registration problem as a minimization of the global robust distance (8) between two segment sets.

A. Feature extraction

1) *Planar regions extraction*: Due to its robustness to noise and outliers, Random Sample Consensus (RANSAC) has

become the most popular method for LiDAR point cloud segmentation. Despite this success, it can generate false segments consisting of points from several nearly co-planar surfaces. Inspired by [1] we have exploited two methods depending on the nature of the data to overcome the RANSAC limitations.

a) *RANSAC Based on Sensor Topology*: For the outdoor scans, acquired by a Mobile Mapping System (MMS), we have access to the sensor topology (adjacency between successive pulses in the same line and between lines). Following [2], we exploit this property to extract compact planar patches.

b) *MSAC*: For the indoor scans, acquired in a static mode, we do not have access to the sensor topology. So, we could not use the RANSAC based on the sensor topology method for the extraction of planar regions. We follow [1] and use a straightforward adaptation of M-estimator Sample Consensus (MSAC) [13], a RANSAC extension that provides a potential solution to the spurious plane problem.

2) *Openings detection*: Inspired by [3], we have performed the detection of the openings in three main steps as shown in figures 2.

a) *Segmentation and facade plane selection*: Most openings have a rectangular vertical shape of a limited extent (a few meters) positioned within a vertical plane (a wall or the facade). So, to efficiently extract them, we need to detect the indoor and the outdoor planes and select the facades. The plane detection step has been done using the methods described in section III-A1 followed by polygons extraction using alpha shape technique [15]. Finally, the vertical large polygons have been selected as the facades.

b) *Evidence of openings detection*: As the LiDAR beams usually cross the facade through openings, we have started by detecting the evidence of openings as the intersection points of these beams and the detected facades using Ray Tracing:

- 1) For each point P_i , we trace a ray R_i from the LiDAR optical center O to this point.
- 2) we find P_i^j , the intersection points of R_i with the supporting planes \mathcal{P}_j of each façade polygon F_j .
- 3) If one P_i^j lies inside the polygon and the distance between P_i and $\mathcal{P}_j > d_{min}$, we add P_i^j to the list E_j of evidences of openings on wall j . we use the threshold d_{min} , in order to exclude noisy points that may still represent points of the facade.

c) *Outline openings extraction*: For each wall plane \mathcal{P}_j the evidences of openings E_j are grouped in vertical rectangles:

- Extract the connected components of E_j with a distance threshold.
- Estimate the minimum bounding rectangle of each component.
- For each rectangle, transform each 2D corner to a 3D point and create the four 3D line segments corresponding to its edges to get a 3D representation of our shape as shown in Figures (3).

The extraction of the connected components happens in a graph whose vertices are the points indicating an evidence of

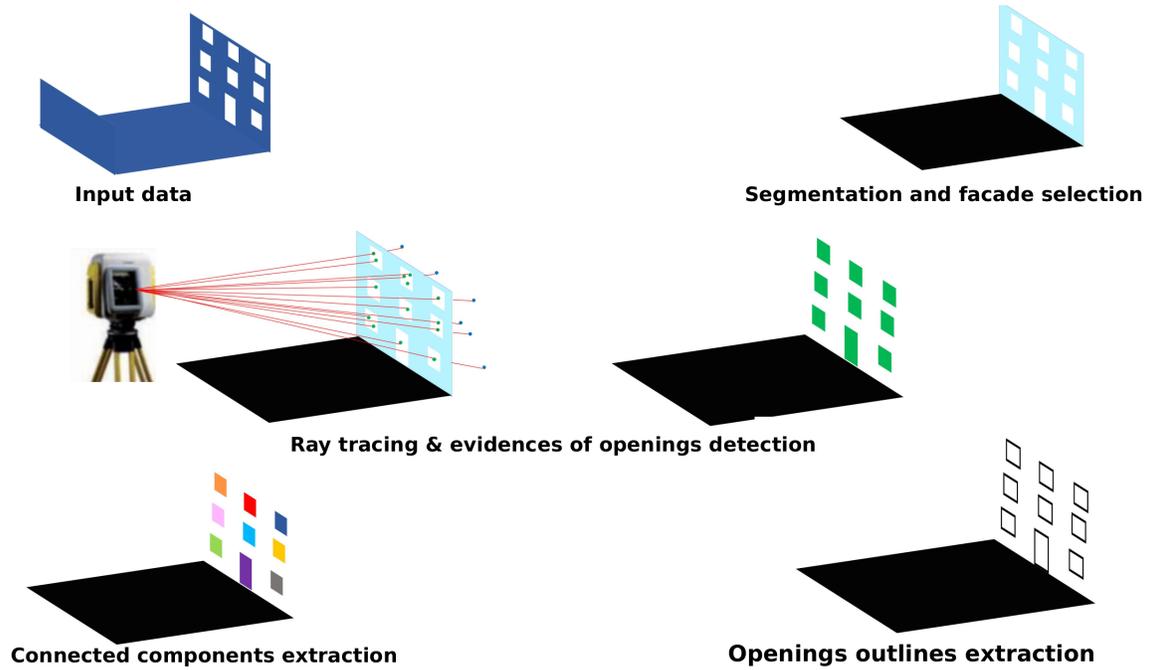


Fig. 2: Illustration of opening detection steps.

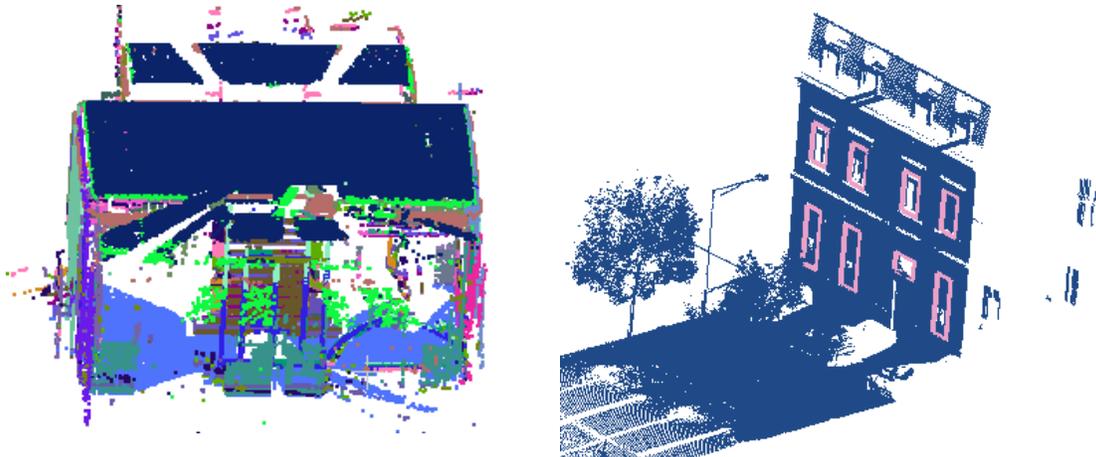


Fig. 3: Feature extraction in LiDAR scans. Left: planar regions detected in an indoor scan. Right: Openings detected in an outdoor scan.

openings and the edges link two points whenever their distance does not exceed a fixed threshold.

B. Feature matching and transformation estimation

1) *Direction clustering*: For each indoor scan, we greedily cluster planes P_i according to their normals \vec{n}_i ordered by decreasing number of inliers n_i (number of points that have a distance to the plane less than a given threshold), using the algorithm proposed in [1], which produces for each scan three clusters: C^h , C^{v_1} and C^{v_2} .

2) *RANSAC minimization*: We proceed as in [2] and apply a RANSAC procedure based on two nested sampling strategies. The first one consists in matching the vertical planes

representing the walls (facades) of the two scans, whereas the second one consists in matching the selected segments in the matched walls. The advantage of integrating these two matching strategies is to simplify the selection of the two pairs of segments and decrease the calculation time of the algorithm by reducing the number of iterations. Each RANSAC iteration consists in the following steps:

- Select a facade plane from each scan, p_1 for indoor plane and p_2 for outdoor plane.
- Make the two planes coincide by applying a rotation R on p_1 around their line of intersection, the result is p'_1
- Randomly selects a corner c_1 (the intersection point of

- a horizontal segment and a vertical segment) from an opening of p'_1 and a corner c_2 from an opening of p_2 .
- Compute the translation component in the plane between the two selected corners, which fixes only two degrees of freedom.
 - Randomly select two planes p_3 and p_4 , each one from an indoor cluster perpendicular to the facade, and transform them.
 - Compute A : the intersection point of p'_1 , p_3 and p_4 ; B : the intersection point of p_2 , p_3 and p_4 .
 - Find the missing degree of freedom of the translation as the vector joining A and B .

IV. LiDAR DATA/BIM MODEL REGISTRATION

A. 3D line segment detection

In this work, we have chosen the algorithm proposed in [4] to extract 3D line segments from LiDAR data. For the BIM model, we use a Poisson disk sampling method [14] to sample points over the whole model and extract the edges from the sampled point cloud with the same method. It is a simple and efficient algorithm that starts by segmenting the point cloud into planar 3D regions via region growing and merging. All the points belonging to the same planar region are projected into the supporting plane of this region to form a 2D image. Then, 2D contour extraction and least square fitting are performed to detect 2D line segments. Finally, these 2D line segments are transformed back into the 3D frame to get the 3D segments.

B. Feature matching and transformation estimation

1) *3D segments directional clustering*: The first step of our pipeline is the clustering of the 3D segments of each dataset according to their direction. This is done using our proposed greedy algorithm described in Algorithm 1. For each input data, we cluster 3D segments L_i according to their direction d_i in decreasing order of length, which produces for each dataset three clusters: C_1^1 , C_2^1 and C_3^1 for the first input data, C_1^2 , C_2^2 and C_3^2 for the second input data. Notice that at step 5, for computing the average direction of a cluster, care must be taken to be invariant to the possibly opposite orientations of the different segments. That is why the sign function is used, so as to orient each direction as much along \mathbf{v}_1 as possible.

2) *Direction cluster association*: We associate each cluster C_1^i with the cluster C_2^j with the smallest angle between the mean direction:

$$A_k = \{C_1^i, C_2^j\}, |\mathbf{d}(C_1^i) \cdot \mathbf{d}(C_2^j)| \geq 1 - \epsilon \quad (9)$$

C. RANSAC minimization

RANSAC has proven its robustness and efficiency as an optimization algorithm in several applications. In this section, we describe a new version of RANSAC based on the selection of double pairs of segments at each iteration. The selected segment pairs define a unique transform. The clusters are used to ensure that these pairs of segments have compatible angles. At each RANSAC iteration:

- We randomly select two cluster associations.

Algorithm 1 Greedy direction clustering

- 1: Input: Set of segments L , each segment $L_i = [A_i B_i]$ has a director vector $\mathbf{v}_i = \overrightarrow{A_i B_i}$, a length $\|\mathbf{v}_i\|$ and a unit direction $\mathbf{d}_i = \mathbf{v}_i / \|\mathbf{v}_i\|$.
- 2: Clusters initialization:
 - $C_1 = \{L_1\}$ where L_1 is the longest segment.
 - $C_2 = \{L_2\}$ where L_2 is the longest one among segments for which $|d_i \cdot d_1| < \cos(\epsilon)$.
 - $C_3 = \{L_3\}$ where L_3 is the longest one among segments for which $\max(|d_i \cdot d_1|, |d_i \cdot d_2|) < \cos(\epsilon)$.
- 3: Mark L_1 , L_2 and L_3 as processed and all other L_i as unprocessed
- 4: Let L_{cur} be the longest unprocessed segment. If there is no unprocessed segment, stop the algorithm, else mark L_{cur} as processed.
- 5: Each cluster C_k has a direction $\mathbf{d}(C_k)$ computed as mean of the directions of the 3D segments in the cluster:

$$\mathbf{d}(C) = \frac{\sum_{L_i \in C} \text{sign}(\mathbf{v}_i \cdot \mathbf{v}_1) \mathbf{v}_i}{\|\sum_{L_i \in C} \text{sign}(\mathbf{v}_i \cdot \mathbf{v}_1) \mathbf{v}_i\|}$$

- 6: Compute $k_{min} = \arg \min_k 1 - |d_{cur} \cdot d(C_k)|$
 - 7: Compute $n_i = 1 - |d_{cur} \cdot d(C_{k_{min}})|$
 - 8: If $n_i < \epsilon$, add L_{cur} to the cluster $C_{k_{min}}$.
 - 9: Go back to step 4.
-

- We randomly select one segment from each associated cluster.
- We compute the transform (rotation and translation) that best aligns the matched 3D segments using the method of Section IV-D.
- For this transform, we estimate the global robust distance between all segments of the two sets using (8).

The final registration is given by the transformation that minimizes the global robust distance.

D. Transform estimation

Once two pairs of segments $\{v_i, v_j\}$ (first selected cluster association) and $\{h_i, h_j\}$ (second selected cluster association) are associated, we estimate the rotation that best aligns the corresponding two 3D lines. Let us call d_v^i, d_v^j, d_h^i and d_h^j the unit director vectors of v_i, v_j, h_i and h_j . We start by creating the orthonormal basis $\mathcal{O}^i = (\mathbf{x}^i, \mathbf{y}^i, \mathbf{z}^i)$, where:

$$\mathbf{x}^i = \mathbf{d}_v^i \quad \mathbf{y}^i = \frac{\mathbf{d}_h^i - (\mathbf{d}_h^i \cdot \mathbf{x}^i) \mathbf{x}^i}{\|\mathbf{d}_h^i - (\mathbf{d}_h^i \cdot \mathbf{x}^i) \mathbf{x}^i\|} \quad \mathbf{z}^i = \mathbf{x}^i \times \mathbf{y}^i$$

We then compute the rotation R that aligns the associated clusters as the base change matrix between \mathcal{O}^i and \mathcal{O}^j :

$$R = \mathcal{O}^j \mathcal{O}^{i^{-1}} \quad (10)$$

To estimate the translation, we start by defining the point-to-line distance:

$$\text{dist}(\mathbf{p}, L = \mathbf{a} + dt) = \frac{\|\mathbf{d} \wedge (\mathbf{a} - \mathbf{p})\|}{\|\mathbf{d}\|} = \|[\mathbf{d}]_{\times} (\mathbf{a} - \mathbf{p})\| \quad (11)$$

assuming that \mathbf{d} is normalized, and again calling $[\mathbf{d}]_{\times}$ the matrix of the cross product with \mathbf{d} . We look for the translation \mathbf{t} that minimizes:

$$\epsilon = \sum_i \|[\mathbf{d}]_{\times}(\mathbf{a}_i - (\mathbf{p}_i + \mathbf{t}))\|^2 \quad (12)$$

The minimum is reached when the gradient is null:

$$\nabla_{\mathbf{t}}\epsilon(\mathbf{t}) = -2 \sum_i [\mathbf{d}_i]_{\times}^t [\mathbf{d}_i]_{\times} (\mathbf{a}_i - (\mathbf{p}_i + \mathbf{t})) = 0 \quad (13)$$

Noting:

$$\mathbf{w} = \sum_i [\mathbf{d}_i]_{\times}^t [\mathbf{d}_i]_{\times} (\mathbf{p}_i - \mathbf{a}_i) \quad M = - \sum_i [\mathbf{d}_i]_{\times}^t [\mathbf{d}_i]_{\times},$$

we get a closed form solution for \mathbf{t} :

$$\mathbf{t} = M^{-1}\mathbf{w} \quad (14)$$

V. EVALUATION AND DISCUSSION

In this work, we were interested in two challenging problems for BIM production and BIM comparison with the as-built data in order to perform progress monitoring.

A. Indoor/outdoor registration

The first part of our contribution consists in proposing a heterogeneous features-based registration algorithm to address the challenging problem of indoor/outdoor registration. Our proposed method takes as attributes a set of openings and planar features. Using the openings we can find the rotation and the translation in the facade plane (two degrees of freedom). We recover the missing degree of freedom for the translation by adding the planes. The best transformation has been selected based on the minimization of the global robust distance between two segment sets. We tested our algorithm on real data, and the obtained results have proved the performance of our algorithm to register the indoor and outdoor scans whatever the initial position as shown in figure 4. As we do not know the ground truth we only considered the visual results. The introduced approach has exceeded the limitations of some existing methods:

- Iterative methods require a good approximation of the initial transformation to be able to converge toward the correct solution.
- Opening-based methods such as the method proposed in [3] have an uncertainty in the direction orthogonal to the facade.

B. LiDAR data/BIM model registration

The second part of our contribution consists in proposing a linear features-based registration algorithm to address the problem of LiDAR data/BIM model registration. The optimal transformation was estimated by minimizing the global robust distance between two sets of 3D segments after extracting them using a state-of-the-art algorithm. We have tested our algorithm on real data corresponding to a construction site in Spain. The obtained results have proved the performance of our method to register the LiDAR data and the model BIM as shown in figure 5.

VI. CONCLUSION AND FUTURE WORK

In this paper, we are interested in two registration problems that remain challenging problems for urban modeling. The first is the indoor/outdoor registration which represents a very important step for BIM production. In order to carry out this kind of registration we have proposed an efficient algorithm based on heterogeneous features (openings and planes). The second is the LiDAR data/BIM model registration which is considered a key step in performing progress monitoring and quality control. The common point of the two proposed solutions consists in the definition of the global robust distance between two segment sets and the minimization of this distance based on the RANSAC paradigm. We can propose some improvements in future works:

- LiDAR data/BIM model registration: extraction of sharp edges on the BIM model and use them as input 3D segments of this model for the registration
- Indoor/outdoor registration: if we can see pieces of the indoor walls parallel to the facade during the outdoor scan, we can detect them as points where the LiDAR beams cross the facade. The extraction of the planes from these points and their integration into our registration framework can give us additional information on the thickness of the facade which can increase the accuracy of the registration.

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REFERENCES

- [1] Djahel, R., Vallet, B., and Monasse, P. (2021). Towards Efficient Indoor/outdoor Registration Using Planar Polygons. ISPRS annals of the photogrammetry, remote sensing and spatial information sciences, 2, 51-58.
- [2] Guinard, S. A., Mallé, Z., Ennafii, O., Monasse, P., and Vallet, B. (2020). Planar polygons detection in lidar scans based on sensor topology enhanced RANSAC. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2, 343-350.
- [3] Djahel, R., Vallet, B., and Monasse, P. (2022). Detecting openings for indoor/outdoor registration. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 43, 177-184.
- [4] Lu, X., Liu, Y., and Li, K. (2019). Fast 3D line segment detection from unorganized point cloud. arXiv preprint arXiv:1901.02532.
- [5] Chen, S., Nan, L., Xia, R., Zhao, J., and Wonka, P. (2019). PLADE: A plane-based descriptor for point cloud registration with small overlap. IEEE Transactions on Geoscience and Remote Sensing, 58(4), 2530-2540.

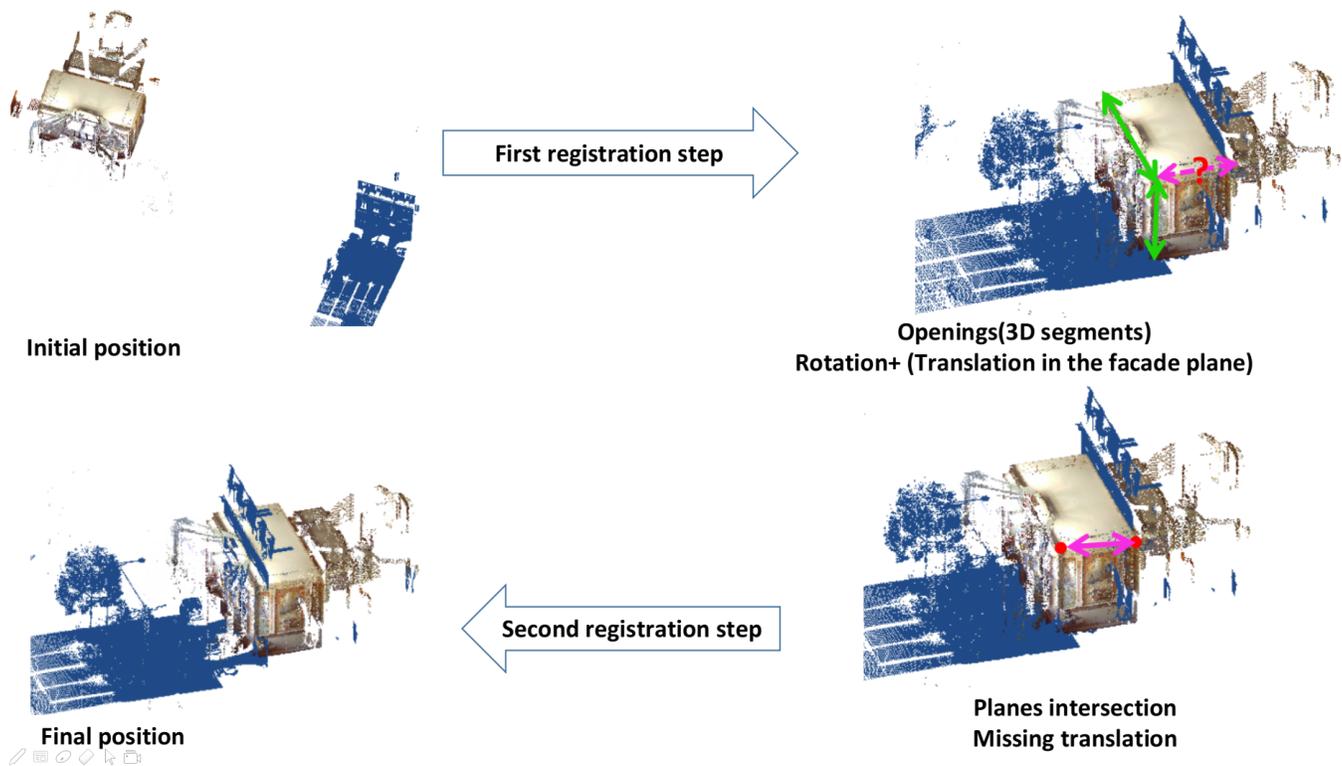


Fig. 4: Indoor/Outdoor registration between two LiDAR scans. Upper-left: the RGB-colored indoor scan is unregistered with the uncolored exterior scan. Upper-right: the RANSAC algorithm recovers the translation in the facade plane (green axes) but leaves the facade breadth undecided (magenta axis). Lower-right: Identifying the two corners from the scans allows registering the scans (lower-left) assuming no facade breadth.

[6] Assi, R., Landes, T., Murtiyoso, A., and Grussenmeyer, P. (2019). Assessment of a key points detector for the registration of indoor and outdoor heritage point clouds. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 42, 133-138.

[7] Yang, Y., Fang, G., Miao, Z., and Xie, Y. (2022). Indoor–Outdoor Point Cloud Alignment Using Semantic–Geometric Descriptor. *Remote Sensing*, 14(20), 5119.

[8] Gruner, F., Romanschek, E., Wujanz, D., and Clemen, C. (2022). Co-Registration of Tls Point Clouds with Scan-Patches and Bim-Faces. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 46, 109-114.

[9] Sheik, N. A., Deruyter, G., and Velaerts, P. (2022). Automated Registration of Building Scan with BIM through Detection of Congruent Corner Points. In *The 7th International Conference on Smart City Applications* (Vol. 48, pp. 179-185). Copernicus GmbH.

[10] Sheik, N. A., Deruyter, G., and Veelaert, P. (2022). Plane-based robust registration of a building scan with its BIM. *Remote Sensing*, 14(9), 1979.

[11] Djahel, R., Monasse, P., and Vallet, B. (2022). A 3D segments based algorithm for heterogeneous data registration. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 43, 129-136.

[12] Djahel, R. (2022). *Registration of Heterogeneous Data for Urban Modeling* (Doctoral dissertation, Marne-la-vallée, ENPC).

[13] Torr, P. H., and Zisserman, A. (2000). MLESAC: A new robust estimator with application to estimating image geometry. *Computer vision and image understanding*, 78(1), 138–156.

[14] Gamito, M. N., and Maddock, S. C. (2009). Accurate multidimensional Poisson-disk sampling. *ACM Transactions on Graphics (TOG)*, 29(1), 1-19.

[15] Edelsbrunner, H., Kirkpatrick, D., and Seidel, R. (1983). On the shape of a set of points in the plane. *IEEE Transactions on information theory*, 29(4), 551-559.

[16] Cohen, A., Schönberger, J. L., Speciale, P., Sattler, T., Frahm, J. M., and Pollefeys, M. (2016). Indoor-outdoor 3d reconstruction alignment. In *ECCV 2016: Proceedings of the 14th European Conference on Computer Vision, Amsterdam, The Netherlands, October 11-14, 2016, Part III 14* (pp. 285-300). Springer International Publishing.

[17] Koch, T., Korner, M., and Fraundorfer, F. (2016). Automatic alignment of indoor and outdoor building models using 3D line segments. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops* (pp. 10-18).

[18] Kaiser, T., Clemen, C., and Block-Berlitz, M. (2022). Co-registration of video-grammetric point clouds with BIM—first conceptual results. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 46, 141-148.

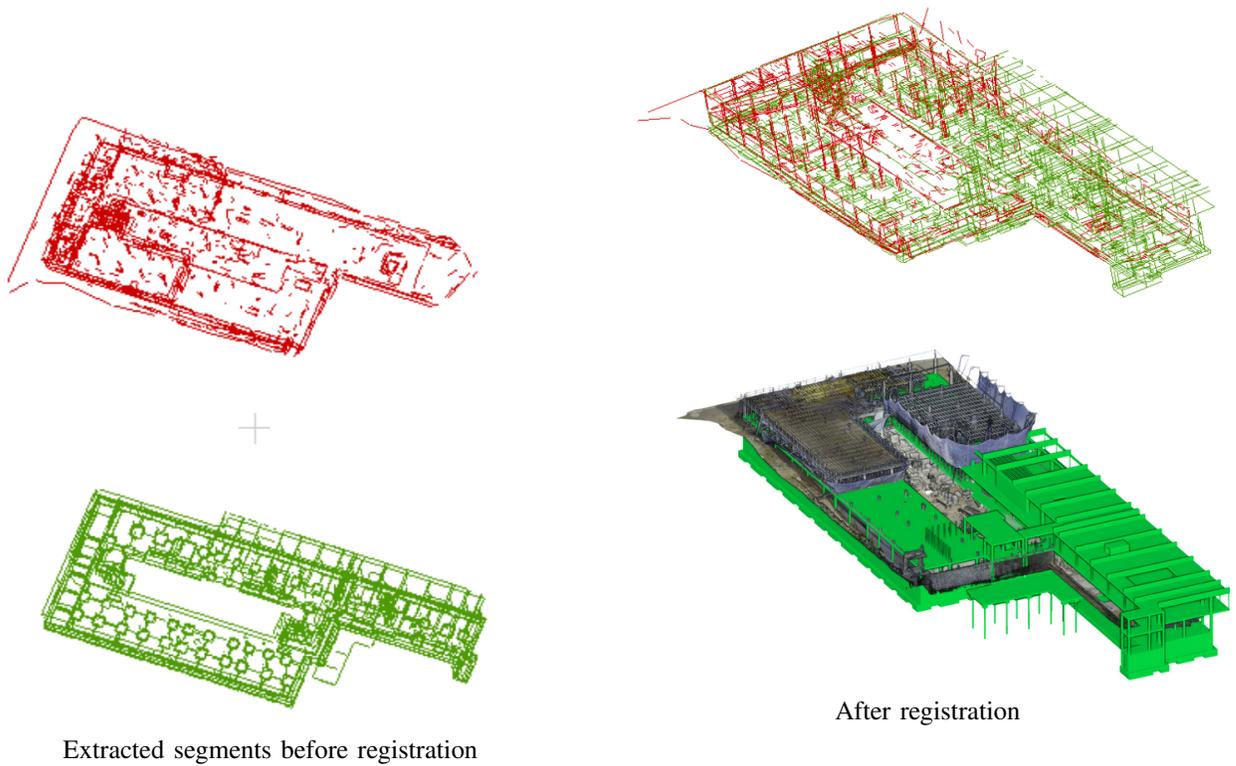


Fig. 5: Lidar data/BIM model registration. Left: the LiDAR scan (red) and the point cloud obtained by sampling the BIM. Right: registered segments and registered LiDAR and BIM.