3DSES: An Indoor Lidar Point Cloud Segmentation Dataset with Real and Pseudo-Labels from a 3D Model

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Abstract: Semantic segmentation of indoor point clouds has found various applications in the creation of digital twins for robotics, navigation and building information modeling (BIM). However, most existing datasets of labeled indoor point clouds have been acquired by photogrammetry. In contrast, Terrestrial Laser Scanning (TLS) can acquire dense sub-centimeter point clouds and has become the standard for surveyors. We present 3DSES (3D Segmentation of ESGT point clouds), a new dataset of indoor dense TLS colorized point clouds covering 427 m^2 of an engineering school. 3DSES has a unique double annotation format: semantic labels annotated at the point level alongside a full 3D CAD model of the building. We introduce a model-to-cloud algorithm for automated labeling of indoor point clouds using an existing 3D CAD model. 3DSES has 3 variants of various semantic and geometrical complexities. We show that our model-to-cloud alignment can produce pseudo-labels on our point clouds with a $> 95\%$ accuracy, allowing us to train deep models with significant time savings compared to manual labeling. First baselines on 3DSES show the difficulties encountered by existing models when segmenting objects relevant to BIM, such as light and safety utilities. We show that segmentation accuracy can be improved by leveraging pseudo-labels and Lidar intensity, an information rarely considered in current datasets. Code and data will be open sourced.

1 INTRODUCTION

Building Information Modeling (BIM) is a comprehensive tool for managing buildings throughout their entire life cycle, from construction to demolition. It consists in creating a digital representation of a building, called a “digital twin”. BIM helps reduce construction and maintenance costs by facilitating planning and simulation on the virtual assets (Bradley et al., 2016) and preserve heritage structures (Pocobelli et al., 2018). BIM allows for monitoring buildings over time and managing equipment by recording details such as installation date and maintenance schedules. The creation of digital twins often involves *in situ* acquisitions to reconstruct the building's 3D structure, often using point clouds (Wang et al., 2015; Jung et al., 2018; Angelini et al., 2017). In recent years, 3D data acquisition technologies have not only significantly improved in accuracy, but also diversified their sensing apparatus. In most cases, sensors create point clouds based either on photogrammetry, *e.g.* using stereo photography or structure-from-motion, or on laser-based Lidar systems. Acquisition has been made increasingly intuitive and easy with the improvements of 3D scanners, including real-time positioning and very high acquisition speed. Terrestrial Laser Scanning (TLS) has become the standard for surveyors to create large point clouds of building interiors in a few hours.

Meanwhile, the enrichment of point clouds has not met the same progresses. 3D CAD modeling of buildings based on point clouds remains a manual and time-consuming task. Creation of 3D CAD models is minimally automated and still requires the intervention of qualified experts. Semantic segmentation of point clouds is a promising avenue to automatically label point clouds, and could accelerate the modeling by helping surveyors to identify structural primi-

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Table 1: Comparison of the characteristics of various point cloud datasets from the literature. Note that 3DSES is the only indoor TLS dataset that includes intensity, point level annotations and a 3D CAD model. Despite its size, it also has more points than most existing datasets, demonstrating a very high point density.

Name	Environment	Classes	Extent[1]	Points (M)	Intensity	3D model	Source
Oakland (Munoz et al., 2009)	Outdoor	44	-	1.6	❌	❌	MLS
Paris-rue-Madame (Serna et al., 2014)	Outdoor	17	160 m	20	✅	❌	MLS
IQmulus (Vallet et al., 2015)	Outdoor	8	10 000 m	12	✅	❌	MLS
Semantic 3D (Hackel et al., 2017)	Outdoor	8	-	4000	✅	❌	TLS
Paris-Lille-3D (Roynard et al., 2018)	Outdoor	9	1940 m	143.1	✅	❌	MLS
SemanticKITTI (Behley et al., 2021)	Outdoor	25	39 200 m	4500	✅	❌	MLS
Toronto-3D (Tan et al., 2020)	Outdoor	8	1000 m	78.3	✅	❌	TLS
Matterport3D (Chang et al., 2017)	Indoor	20	219 399 m^2	-	❌	❌	Camera
ScanNet (Dai et al., 2017)	Indoor	20	78 595 m^2	242	❌	❌	Camera
S3DIS (Armeni et al., 2016)	Indoor	13	6020 m^2	215	❌	❌	Camera
ScanNet++ (Yeshwanth et al., 2023)	Indoor	-	15 000 m^2	20	❌	❌	TLS
ScanNet200 (Rozenberszki et al., 2022)	Indoor	200	78 595 m^2	242	❌	❌	Camera
LiDAR-Net (Guo et al., 2024)	Indoor	24	30 000 m^2	3600	✅	❌	MLS
3DSES Gold 🥇	Indoor	18	101 m^2	65	✅	✅	TLS
3DSES Silver 🥈	Indoor	12	304 m^2	216	✅	✅	TLS
3DSES Bronze 🥉	Indoor	12	427 m^2	413	✅	✅	TLS
Indoor Modelling (Khoshelham et al., 2017)	Indoor	❌	2824 m^2	127	❌	✅	5 sensor
Craslab (Abreu et al., 2023)	Indoor	❌	417 m^2	584	✅	✅	TLS

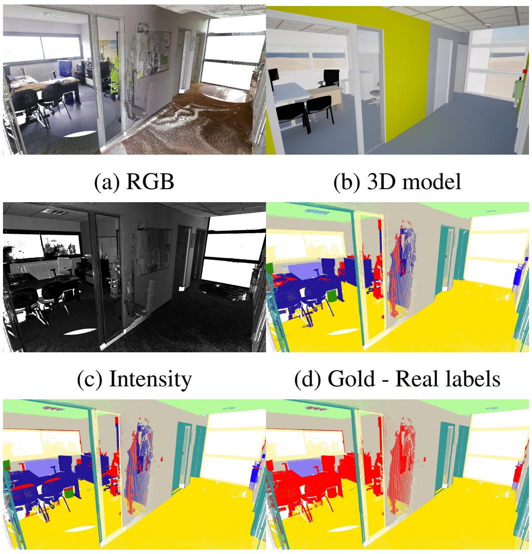
[1] Surface for indoor datasets, linear extent for outdoor datasets.

tives (walls, ground, doors) and even furniture types (chairs, tables, etc.). However, few datasets exist for semantic segmentation of indoor TLS point clouds. Moreover, surveying companies have access to large databases of existing 3D CAD models and associated point clouds, but the latter are mostly unlabeled. For these reasons, we introduce 3DSES (Fig. 1), a dataset of indoor TLS acquisitions with manually annotated point clouds and a BIM-like 3D CAD model. In addition to the overall structure and furniture, we label several types of common BIM elements, such as extinguishers, alarms and lights, that are challenging to detect in point clouds. To evaluate the feasibility of automatically annotating point clouds based on existing BIM models, we introduce a 3D model-to-cloud alignment algorithm to label points clouds. We show that these pseudo-labels are nearly as effective as manual point cloud annotation for most classes. However, we show that small objects remain extremely challenging for existing point cloud segmentation models. 3DSES is a unique dataset that contains all the steps required for automated scan-to-BIM: dense point clouds, semantic segmentation labels and a full 3D CAD model. We hope that 3DSES will enable the creation and testing of deep models for multiple tasks, from point cloud segmentation to BIM generation through mesh to point cloud alignment.

2 PREVIOUS WORK

Numerous datasets exist for semantic segmentation of point clouds with various sizes of scenes, different types of objects of interest and acquired using various sensors, each with their own characteristics. We review in Table 1 some of the more popular ones.

Outdoor Datasets. The first popular datasets for semantic segmentation of point clouds focused on outdoors. Mobile laser scanning is popular for outdoor scenes as moving platforms cover more ground. Since the laser is moving, the point clouds tend to be sparse, *e.g.* the seminal Oakland dataset (Munoz et al., 2009) has less than 2M points. Later datasets such as IQmulus (Vallet et al., 2015) or Paris-rue Madame (Serna et al., 2014) are also relatively small, with less than 20M points. Bigger datasets have been consolidated by covering larger scenes, such as Paris-Lille-3D (Roynard et al., 2018) and SemanticKITTI (Behley et al., 2021). While MLS makes sense for



(a) RGB (b) 3D model

(c) Intensity (d) Gold - Real labels

(e) Gold - Pseudo labels (f) Silver - Pseudo labels

Figure 1: Modalities and annotation variants of 3DSES. Gold real labels are manual annotations across 18 classes, including small objects such as light switches and electrical outlets. Pseudo-labels are obtained by automatically aligning the 3D model on the point cloud, introducing some noise in the annotation (see *e.g.* the top of the chairs). Silver labels use a simplified classification of only 12 categories (*e.g.* the wastebin is now simply "clutter"). Legend: Column in dark purple, components in dark green, coverings in light green, doors in green, emergency signs in light blue, fire terminals in dark blue, heaters in light purple, lamps in blue, ground in yellow, walls in grey, windows in light yellow, clutter in red.

autonomous driving, segmentation performance on these point clouds is not representative of indoor scenes which are much denser with lots of small objects. Concurrently, point clouds acquired by aerial Lidar have been used to create datasets on very large scenes, such as the ISPRS 3D Vaihingen (Rottensteiner et al., 2012), DublinCity (Zolanvari et al., 2019), LASDU (Ye et al., 2020), DALES (Varney et al., 2020), Campus3D (Li et al., 2020), Hessigheim (Kölle et al., 2021), SensatUrban (Hu et al., 2021) and FRACTAL (Gaydon et al., 2024). These datasets use Aerial Laser Scanning (ALS), with a top-down view that makes them effective for digital surface models but unsuitable for BIM.

However, some outdoor datasets have a density and geometry close to those found in BIM. For example, Semantic 3D (Hackel et al., 2017) and Toronto-3D (Tan et al., 2020) both use TLS with high point density. These outdoor scenes do not contain many small objects, though, as they rarely consider classes smaller than outdoor furniture, *e.g.* benches or trashbins.

Indoor Datasets. Few new indoors datasets have been published in the last five years. The two most widely used datasets – S3DIS (Armeni et al., 2016) and ScanNet (Dai et al., 2017) – were published in 2017. The lesser known Matterport3D (Chang et al., 2017) was published in the same year with similar characteristics. ScanNet was updated with more classes in ScanNet200 (Rozenberszki et al., 2022), yet using the same point clouds. All these datasets are acquired by RGB-D cameras. The resulting point clouds are sparser and more sensitive to occlusions than TLS data. For example, S3DIS contains 215 million points, which corresponds to approximately ten stations in a medium-resolution TLS system. Yet, these datasets are the most common benchmarks to evaluate deep point cloud segmentation, meaning that new approaches are tested on partially obsolete technology. While indoor TLS datasets exist, *e.g.* Indoor Modeling (Khoshelham et al., 2017) and Craslab (Abreu et al., 2023), they do not contain semantic labels and only release a simplified CAD model. LiDAR-Net (Guo et al., 2024) uses a mobile laser scanner (MLS) to create an indoor dataset more suitable for autonomous navigation, resulting in a point cloud that contains scan holes, scan lines and various anomalies that are not shared with TLS scans for building surveys. To the best of our knowledge, the only dataset using labeled TLS point clouds is ScanNet++ (Yeshwanth et al., 2023). However, ScanNet++ used a complex three devices acquisition setup. DSLR images were acquired separately from the scans, and then backprojected to colorize point clouds. This setup is not representative of usual surveys practices. For 3DSES, we use a simpler acquisition workflow, as the RGB information comes directly from the TLS.

Points Clouds with Intensity. Lidar intensity measures the strength of the laser impulse returned by a scanned point. It is a feature commonly used in outdoor point cloud datasets, especially because infrared is helpful to identify vegetation. However, intensity is notably absent from indoor datasets, with the exception of LiDAR-Net (Guo et al., 2024). In theory, different materials reflect light differently and these variations impact the measured intensity of the laser echo. This information might help deep models to discriminate between objects that have similar geometry, but different natures. For this reason, we include the intensity information in our 3DSES dataset.

Uniqueness of 3DSES. While covering a smaller surface than other datasets, 3DSES is extremely dense, with a sub-centimeter resolution. It is also the only TLS dataset with Lidar intensity, an information often removed in publicly available datasets, despite theoretically being a discriminative property of materials. 3DSES is also a *labeled* dataset, suitable to train or evaluate semantic segmentation algorithms. Finally, 3DSES comes with a 3D CAD model designed for BIM. This combination is unique across existing datasets, and makes 3DSES suitable to investigate 3D point clouds for indoor building surveys and modeling.

3 3DSES

We present in this section the data acquisition and labeling process, the 3D modeling and an automated pseudo-labeling alignment algorithm.

3.1 Data Collection

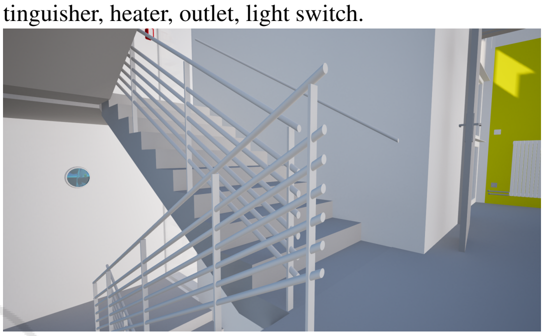
Point Clouds Acquisition. Data acquisition was carried out at ESGT using two Terrestrial Laser Scanners (TLS): a Leica RTC360 and a Trimble X7. High-resolution pictures were taken for each scan (15MP for RTC360 and 10MP for Trimble X7). Scans were preregistered during the survey. We performed and bundled multiple scans inside every room to capture as many objects as possible. Scans were then merged for registration, and any missing link was manually corrected. Point clouds are georeferenced using coordinates from total stations and GNSS. We release both colorized (Fig. 1a) and intensity (Fig. 1c) clouds.

Manual Labeling. We manually annotated the point clouds to create a ground truth denoted as the *real labels*, shown in Fig. 1d. Since this is time-consuming, we annotated only 10 points clouds in 18 fine-grained classes: “Column”, “Component”, “Covering”, “Damper”, “Door”, “Exit sign”, “Fire terminal”, “Furniture”, “Heater”, “Lamp”, “Outlet”, “Railing”, “Slab”, “Stair”, “Switch”, “Wall”, “Window” and a “Clutter” class that encompasses all points not belonging to another class. Labels were annotated in two passes: 1) labeling by a single annotator (30 to 40 minutes per scan, depending on the complexity of the point cloud, the number of points and the diversity of represented objects); 2) verification pass by an experienced annotator (20 to 30 minutes per scan).

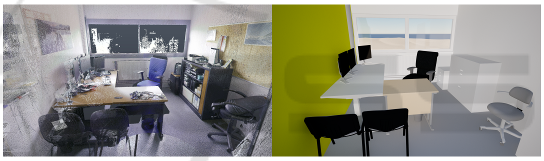
We then annotated 20 additional point clouds with a simpler taxonomy of only 12 classes, shown in Fig. 1f. These labels were annotated in a single pass, as the target objects are less ambiguous with simpler geometries. During this process, the points clouds were partially cleaned of outliers and far away points.

3D CAD Model. Each type of object is tagged as a member of the corresponding IFC (Industry Foundation Classes) family. The geometry of structural elements (walls, floors, roofs, etc.) is accurately modeled, *i.e.* shapes and dimensions are modeled as precisely as possible. Furniture, such as tables and chairs, and utilities, such as fire extinguishers and emergency exit signs, use standard models, *e.g.* all chairs use the same mesh (cf. Fig. 2d). This is a common practice in BIM, as defining a separate “chair” family for each instance would be too time-consuming. Fig. 2e illustrates how these generic 3D

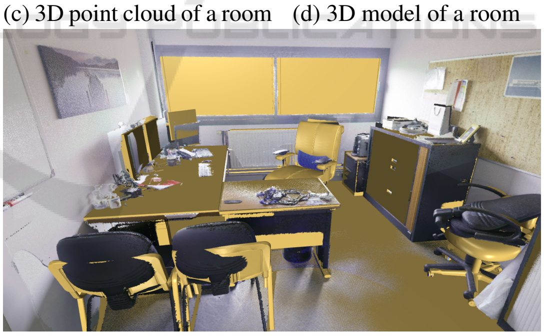
(a) Example of modeled 3D systems: fire alarm, fire extinguisher, heater, outlet, light switch.



(b) Structural objects: stairs, railings, doors, walls, floors.



(c) 3D point cloud of a room (d) 3D model of a room



(e) Overlay of clouds and objects

Figure 2: View of a test area room. The generic 3D models are close, but not perfect matches for the actual scans.

CAD models create slight geometrical discrepancies between the point cloud and the model. Finally, a special care is given to doors, that can appear either open or closed in scans. We model each door in its correct state depending on its true position in the point cloud. Complete modeling took slightly less than 30 hours.

3.2 Dataset Variants

Based on the TLS scans and the manual annotations, we built three versions of the 3DSES dataset (cf. Table 2). The Gold version is composed of the 10 scans annotated in 18 classes. We consider it to be the "gold standard", using fine-grained high quality real labels. We then extended it into a Silver version that contains all the Gold data and an additional 20 scans. Silver labels use a simplified taxonomy of only 12 classes, that are less time consuming to produce. Both Gold and Silver variants of 3DSES are high quality, using a real ground truth and cleaned up point clouds. Finally, we deliver a Bronze version that includes 12 more scans. Bronze contains the raw point clouds and not the processed and cleaned clouds. These full point clouds are denser and noisier, but also more representative of actual field scans. Since the additional point clouds have not been manually labeled, the Bronze dataset uses the automatically generated pseudo-labels based on the 3D model using the procedure detailed in Section 3.3.

Note that all variants suffer from class imbalance, as shown in Figs. 3a and 3b. Structural elements are over represented compared to other classes, especially furniture and utilities, that are comprised of smaller objects. This is a well-known issue in indoor datasets, such as S3DIS (Armeni et al., 2016), which has 10× more wall points than window points, and ScanNet200 (Rozenberszki et al., 2022), which contains 51 million wall points and only 50 000 fire extinguisher points.

Train/Test Split. We define a set Train/Val/Test split with a common test area to all variants, based on 3 scans located in the Gold section (scans S170, S171 and S180). It contains ≈ 20.7 million points with real ground truth. This allows us to evaluate models on real labels only, whether they have been trained on real or pseudo-labels. Ground truth labels on the test set are kept hidden for later use in a Codabench challenge.

3.3 Pseudo-Labeling from the 3D Model

One of our goals is to evaluate the feasibility of using existing 3D CAD models to label automatically point clouds for semantic segmentation. Pseudo-labels could help leverage existing databases of surveyed buildings that have been scanned and modeled, but not annotated at the point level. To this end, we design an alignment algorithm to map the 3D model on a point cloud.

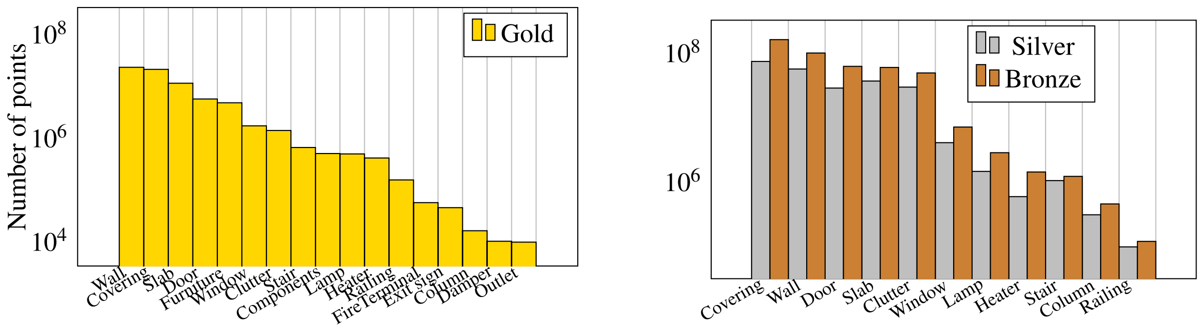
First, we divide our 3D CAD model into objects. This allows us to separate individual instances of walls, heaters, light switches and so on. For each object, we produce the corresponding 3D mesh. Since the 3D CAD model and the point cloud are georeferenced, we can compute a mesh-to-cloud distance for every point in the point cloud. For each object, we first compute its georeferenced bounding box. Then, we compute the distance for each point inside the bounding box to the mesh of the object using the Metro algorithm (Cignoni et al., 1998), implemented in CloudCompare (Girardeau-Montaut, 2006). All points that are inside the mesh are labeled the same class as the IFC family of the object the mesh is derived from. To alleviate for geometrical discrepancies between the mesh and the point cloud, points outside the mesh are assigned to their closest mesh as long as the distance is lower than a predefined threshold. We then repeat this process for all objects. Remaining points that have not been labeled are classified as "clutter". This covers objects that are present in the scan, but have not been modeled, *e.g.* jackets on chairs, books and papers on tables, etc.. The algorithms runs in around 9 hours on CPU to align the full dataset (Bronze). This means the pseudo-labeling process (3D model + alignment) takes ≈ 40 hours. In comparison, manual point cloud annotation takes 1 hour per scan on average, *i.e.* would have taken 42 hours for 3DSES Bronze, including quality check. While these times are comparable, point clouds are intermediate products in indoor surveys, the end goal of which is almost always the production of a 3D CAD model. This is why we assess whether pointwise labels can be obtained as a "free" byproduct, without any additional time dedicated to point annotation.

Evaluation of the Pseudo-Labels. Since 3DSES also includes real labels, we can evaluate how well the pseudo-labels match the ground truth. To do so, we computed some standard segmentation metrics, *i.e.* Intersection over Union (IoU), mean Accuracy (mAcc) and Overall Accuracy (OA). We used different confidence thresholds depending on the object class:

- Gold: 4 cm for all classes, except for "Door", "Furniture", "Window", for which we used 10 cm, due to larger uncertainties when modeling;
- Silver and Bronze: 4 cm for all classes, except for "Door" (10 cm) and "Window" (15 cm).

Table 2: Characteristics of the three variants of the 3DSES dataset.

Variant	Scans	Points	Ground Truth	Pseudo-labels	Features	Classes
Gold 🥇	10	65 214 193	✅	✅	RGB & I	18
Silver 🥈	30	216 181 580	✅	✅	RGB & I	12
Bronze 🥉	42	413 486 927	❌	✅	RGB & I	12



(a) Real labels distribution (Gold).

(b) Pseudo-labels (Silver/Bronze).

Figure 3: Distribution of the real and pseudo labels in the variants of the 3DSES dataset.

Metrics are computed between pseudo-labels and the manual ground truth over the full dataset. We report the alignment metrics in Table 3. We obtain high-quality pseudo-labels on Gold version with $\approx 70\%$ mIoU and 95% accuracy. Structural classes ("Covering", "Slab", "Wall") are very well annotated, with a >90 % score. This is expected as these entities have regular shapes with a fine alignment between the 3D model and the point cloud. The lowest scores are on the "Outlet" and "Switch" classes, below 50 %.

Alignment on the Silver variant is also satisfactory with $\approx 75\%$ mIoU and $> 96\%$ accuracy. Metrics are higher on Silver since it focuses on structural classes that are generally easier to align. The IoU for "Column" is also the lowest due to the use of a slightly too small column diameter in the CAD model. The second worst score is for "Window' with 69 %, as Silver contains more window types, including frames that deviate from the CAD model. Finally, metrics on "Railing" and "Stair" are identical on Gold and Silver, since stairs cover the same area in both datasets.

4 EXPERIMENTS

To assess the difficulty of 3DSES, we evaluate initial baselines for the three variants: Gold, Silver and Bronze. We opt for PointNeXt (Qian et al., 2022) and Swin3D (Yang et al., 2023), since they are some of the highest performing models for semantic segmentation on S3DIS (Armeni et al., 2016), and their code is available. We compare PointNeXt-S (800 000 parameters) to Swin3D-L (68M parameters).

Note that these models both perform voxelization and therefore do not benefit from the extremely high point density of 3DSES. In particular, PointNeXt is not designed to process dense point clouds in optimum time ($\approx$ 4 hours per scan). To reduce inference times, we subsample our test point clouds to 1 cm. We expect that future models evaluated on 3DSES will better take into account the fine resolution of indoor TLS scans.

Hyperparameters. We train Swin3D-L with AdamW, a cosine learning rate for 100 epochs, a batch size of 6, and an inverse class frequency weighted cross-entropy to deal with class imbalance. PointNext-S is trained with the original S3DIS hyperparameters: epochs = 100, batch size = 32, AdamW optimizer, a CosineScheduler and a non-reweighted CrossEntropyLoss. We only tune the learning rate to $l_r = 0.05$ (instead of 0.01 in original setup). Following standard practices (Wang et al., 2017; Wu et al., 2022; Yang et al., 2023), we use test-time augmentation and aggregate segmentation predictions with a majority vote over 12 rotations. Models are trained on an NVIDIA RTX A6000

Results on 3DSES Gold. We train both Swin3D-L and PointNeXt-S models on 3DSES Gold: one on the real labels and the other on the pseudo-labels. All models are evaluated on the ground truth over the test area. Results are reported in Table 4. We observe that 3DSES is a challenging dataset: mean IoU is heavily penalized by performance on small objects. Classes comprised of small objects with few points ($< 10^5$

Table 3: Evaluation of the accuracy of the pseudo-labels obtained using our alignement algorithm on 3DSES. Intersection over Union (IoU) per class, mean IoU (mIoU), overall accuracy (OA) and average accuracy (AA).

Variant	Column	Components	Covering	Damper	Door	Exit sign	Fire terminal	Furniture	Heater	Lamp	Outlet	Railing	Slab	Stair	Switch	Wall	Window	Clutter	OA	AA	mIoU
Gold	21.00	80.96	95.95	77.29	91.95	73.16	86.57	79.48	91.08	66.71	37.59	58.52	95.05	59.07	45.66	93.64	64.55	36.44	94.66	83.09	69.70
Silver	25.02	❌	97.99	❌	93.97	72.27	❌	❌	82.22	73.88	❌	58.52	96.20	59.07	❌	91.52	56.67	88.88	96.37	83.40	74.68

Table 4: Segmentation metrics on the test set for 3DSES Gold, either with real or pseudo labels (and intensity features or not). Intersection over union (IoU) per class, mean IoU (mIoU), overall accuracy (OA), average accuracy (AA).

	Real labels	Intensity	Column	Components	Covering	Damper	Door	Exit sign	Fire terminal	Furniture	Heater	Lamp	Outlet	Railing	Slab	Stair	Switch	Wall	Window	Clutter	OA	AA	IoU
Swin3D	✅	❌	0.00	31.16	90.12	14.63	75.95	12.19	56.67	71.57	76.18	26.76	9.53	71.75	87.63	70.59	0.00	88.40	47.26	52.03	89.74	78.30	49.02
	✅	✅	0.00	49.76	94.62	18.23	81.87	27.37	67.10	73.13	83.61	47.73	0.00	57.31	85.29	56.67	0.00	89.68	53.54	50.46	91.64	74.45	52.02
	❌	❌	17.52	34.81	88.90	31.71	75.84	16.31	48.28	68.87	71.04	24.50	12.85	45.53	86.84	58.64	0.93	87.09	50.59	40.31	88.54	76.80	47.81
	❌	✅	30.06	51.07	93.29	63.98	54.16	0.00	21.36	51.32	66.14	41.09	6.33	50.31	79.04	40.46	0.00	83.92	48.96	31.98	86.48	74.10	45.19
PointNeXt-S	✅	❌	0.00	0.00	96.27	0.00	35.43	0.00	0.00	32.84	0.00	69.12	0.00	0.00	90.87	60.40	0.00	74.58	38.05	24.80	82.58	35.04	29.02
	✅	✅	0.00	56.16	96.73	0.00	65.80	0.00	0.00	52.57	26.59	72.78	0.00	60.75	94.28	85.93	0.00	86.76	59.78	39.47	91.19	49.25	44.31
	❌	❌	0.00	0.01	96.01	0.00	37.57	0.00	0.00	45.11	0.00	39.76	0.00	0.00	89.73	60.33	0.00	77.57	1.18	20.33	84.19	30.48	25.98
	❌	✅	0.00	50.10	96.68	0.00	67.86	0.00	0.00	49.83	43.32	65.51	0.00	7.51	93.79	81.23	0.00	86.27	55.81	21.35	90.08	44.86	39.96

points) are difficult to learn and the model either never predicts them, or makes significant errors. Note that despite its high intraclass variance, "Clutter" is mostly well segmented with a $>50\%$ IoU, showing that the model is able to automatically identify most irrelevant objects from the point clouds. Interestingly, the results also show that Swin3D only slightly underperforms when trained on the pseudo-labels, with a 1.2% decrease in mIoU (47.8% vs. 49.0%) compared to the model trained on the real labels. Segmentation errors when using pseudo-labels are concentrated on classes for which the alignment procedure showed weaknesses, such as "Stair" and "Railing". This demonstrates the potential of using CAD models to automatically label point clouds, as way of circumventing the lack of annotated datasets for specialized settings (*i.e.* factories, schools or administrative buildings…). PointNext struggles with 3DSES and achieves low mIoU scores. However, the same trends hold with better segmentation of structural elements and underperformance on minority classes.

Results on Silver/Bronze. We report in Table 5 the segmentation metrics on the 3DSES test set when training Swin3D and PointNext on Silver, both with pseudo and real labels, and on Bronze with pseudo labels. We observe that metrics are consistently higher for all 12 classes on Silver with real label compared to training the Gold subset. This is expected, since the Silver classification is simpler and removes small objects that were heavily penalized. Yet, the larger training set (Silver is $3\times$ as large as Gold) benefits the segmentation, with higher scores on the "Lamp", "Window" and "Clutter" classes that exhibit strong diversity. Training with pseudo-labels on Silver results in a significant performance drop, correlated with the lower class alignment scores discussed in Section 3.3. Yet results on 3DSES Bronze show that the noise in the pseudo-labels can be alleviated by a larger dataset. Despite using raw point clouds and error-prone pseudo-labels, models trained on Bronze achieves similar (PointNeXt) or even better (Swin3D) segmentation accuracy than when trained on the clean Silver dataset. We assume that diversity partially compensates for label noise, allowing models to learn better invariances despite small errors in the labels. In addition, the raw point clouds are denser that the clean versions used in Silver and Bronze and might provide more geometrical information that is more costly to process, but also more discriminative. These observations show the tradeoffs of the three variants of 3DSES, from training on small high-quality data, to larger but noisier point clouds.

Impact of Lidar Intensity. As described in Section 2, 3DSES is the only indoor TLS dataset that provides Lidar intensity. We included intensity as an additional feature in our models to evaluate its impact on semantic segmentation. As shown in Table 4 for Swin3D, we observe a 3.0% increase in mIoU when using intensity in addition to color on real labels. Nonetheless, we observe a decrease for Swin3D

Table 5: Segmentation metrics on the test set for 3DSES Silver and Bronze, either with real or pseudo labels (and intensity features or not). Intersection over union (IoU) per class, mean IoU (mIoU), overall accuracy (OA), average accuracy (AA).

Model	Variant	Labels	Intensity	Column	Covering	Door	Exit sign	Heater	Lamp	Railing	Slab	Stair	Wall	Window	Clutter	**OA**	**AA**	**IoU**
Swin3D	Silver	✅	❌	0.00	89.07	76.40	9.93	74.69	32.24	46.22	86.40	67.75	89.24	54.62	90.42	91.69	84.84	59.75
		✅	✅	5.40	94.35	83.06	9.30	75.27	44.04	37.63	84.08	38.69	85.34	54.99	72.83	90.47	83.39	57.08
		❌	❌	25.47	88.50	61.62	12.96	59.24	30.79	35.94	77.55	36.22	87.61	48.76	71.15	87.49	88.44	52.98
		❌	✅	52.31	95.82	89.01	11.79	65.29	55.28	64.17	82.06	34.32	92.44	54.00	91.92	93.46	89.44	65.70
	Bronze	❌	❌	51.76	95.90	89.37	12.45	65.80	52.25	82.14	86.80	43.15	93.33	60.53	93.59	94.59	93.67	68.92
		❌	✅	59.68	95.97	88.10	41.80	71.59	55.59	77.20	85.81	41.40	93.00	60.89	94.52	94.51	94.37	72.13
PointNeXt-S	Silver	✅	❌	0.00	96.77	67.11	0.00	16.45	69.95	61.75	94.88	83.87	89.26	62.54	80.25	93.30	66.27	60.24
		✅	✅	0.00	97.07	76.66	0.00	38.73	78.11	65.26	94.85	86.97	90.84	67.08	84.35	94.63	70.59	64.99
		❌	❌	0.00	96.53	73.07	0.00	20.33	66.71	2.79	93.50	76.90	90.32	40.60	71.12	92.68	57.60	52.66
		❌	✅	58.44	96.55	69.81	0.00	33.96	67.00	38.90	93.86	83.48	88.12	51.25	73.60	92.58	71.19	62.91
	Bronze	❌	❌	11.21	95.68	85.16	0.00	69.18	66.19	15.97	93.53	80.09	92.62	49.09	82.86	94.57	66.47	61.79
		❌	✅	56.45	96.44	81.39	0.00	79.71	77.40	42.25	93.35	78.33	91.57	56.47	80.94	94.47	77.06	69.53

on pseudo-labels (2.6%). However, the drop is not consistent on all classes, *e.g.* few classes obtain better IoU. On the other hand, including the intensity for PointNeXt improves mIoU by 15%. This shows that intensity helps generalization of smaller models. In Table 5, intensity helps Swin3D and PointNeXt in most cases. In comparison, Swin3D trained on Silver variant with pseudo-labels and intensity obtains *better* scores (+12.7% IoU) than without intensity. Overall, the preliminary results could indicate that Lidar intensity can indeed be discriminative for some classes, especially for larger datasets. Further experiments are required to validate these observations.

5 CONCLUSION

We introduced 3DSES, a new dataset for semantic segmentation of dense indoor Lidar point cloud. 3DSES fills the need for indoor TLS datasets designed for building survey and modeling. It contains a unique combination of point cloud labels for semantic segmentation, a georeferenced 3D CAD model with BIM oriented objects and Lidar intensity, a radiometric feature not provided in existing datasets. We demonstrate that using 3D CAD models to automatically annotate point clouds is a time-efficient strategy that produces pseudo-labels with 95% accuracy compared to a manual ground truth. Moreover, we show that training on pseudo-labels achieves similar performance to training on real ones on 3DSES. We show that segmentation accuracy can benefit from Lidar intensity in indoor settings, despite radiometry being often ignored in previous works. Segmentation results demonstrate that 3DSES is a challenging new dataset, especially for BIM-oriented classes, *e.g.* small building components such as electrical terminals and safety systems. We hope this new dataset will stimulate research on indoor point clouds processing and motivate the community to investigate auto-modeling tasks in scan-to-BIM.

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