

PCEDNet : A Neural Network for Fast and Efficient Edge Detection in 3D Point Clouds

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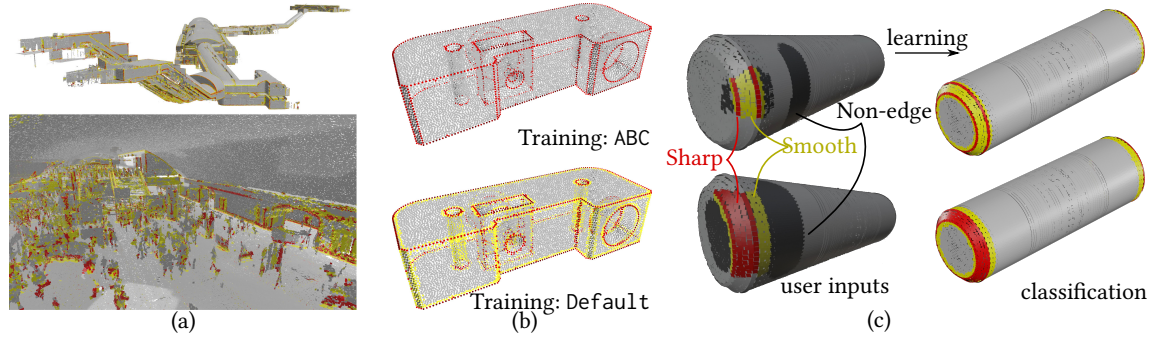


Fig. 1. Three examples of edge detection in point clouds by our PCEDNet neural network. It handles both: (a) the imperfect edges of large scale scans (here 12 million vertices) subject to irregular sampling and noise while detecting both sharp (in red) and smoother (in yellow) edges in few minutes (here less than 6) - and - (b) accurate CAD data on which it can focus on sharp edges if desired, in a few seconds for this model. (c) Our network can also be trained in a few seconds to detect edges following the edge definition provided by a user in an interactive model annotation. We show two annotations corresponding to different user expectations. Most of the processing is precomputed and at runtime edges of this model are classified in less than a second.

In recent years, Convolutional Neural Networks (CNN) have proven to be efficient analysis tools for processing point clouds, e.g., for reconstruction, segmentation and classification. In this paper, we focus on the classification of edges in point clouds, where both edges and their surrounding are described. We propose a new parameterization adding to each point a set of differential information on its surrounding shape reconstructed at different scales. These parameters, stored in a *Scale-Space Matrix (SSM)*, provide a well suited information from which an adequate neural network can learn the description of edges and use it to efficiently detect them in acquired point clouds. After successfully applying a multi-scale CNN on SSMs for the efficient classification of edges and their neighborhood, we propose a new neural network architecture outperforming the CNN in learning time, processing time and classification capabilities. Our architecture is compact, requires small learning sets, is very fast to train and classifies millions of points in seconds.

CCS Concepts: • **Computing methodologies** → **Point-based models**; **Shape Analysis**; *Neural networks*.

Additional Key Words and Phrases: Point clouds, neural networks, edge detection, datasets

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1 INTRODUCTION

Nowadays, acquired point clouds are a very common and widespread representation. The large range of acquisition devices and Computer Vision techniques massively generate clouds with tens or hundreds of millions of points. The shapes sampled by these large unstructured data are arbitrarily complex, and their processing remains extremely tedious. Edges are fundamental features for processing point clouds and their automatic detection is thus useful in a wide range of applications in the fields of computer vision (e.g. feature extraction), computer graphics (e.g. contour line reconstruction) and others. Despite regular advances over the years, it remains however an open, very challenging problem.

In general, edges are defined strictly as sharp edges, e.g. for manufactured objects [Koch et al. 2019], or as feature lines in an object. When asked to draw feature lines, users tend to follow more complex rules that may vary from people to people [Cole et al. 2008]. This leads to a lack of clear theoretical definition of an edge, especially on 3D surfaces acquired from models including features of different scales and more or less damaged/clean edges (e.g. stone or plastered buildings, progressively smoothed edges, polished mechanical parts, etc). In addition, an edge can be considered as sharp or smooth depending on the observation scale. This generates contextualized and potentially ambiguous interpretation of what edges are. For instance, different persons produced different annotations on the models provided for the recent feature curve detection contest [Thompson et al. 2019]. These models include a large variety of different edges, from sharp to smooth and rounded. This underlines that the frontier between an edge and a smooth surface (i.e. a feature boundary and a feature continuity) remains subjective, especially in the case of real world models.

Machine Learning (ML) approaches have gain a lot of interest for their ability to efficiently reproduce theoretically “fuzzy” or complicated classifications for which we are able to provide a sufficiently large set of annotated data. At first glance, they thus seem particularly attractive to create efficient edge detectors. However, in the context of point cloud processing, ML remains very challenging to use as there is neither natural ordering [Zaheer et al. 2017] nor intrinsic parameterization of the input data. In the past years, patches of points have been used by several approaches to apply Convolution Neural Networks (CNN) for classification [Qi et al. 2016a] and local shape property estimation [Guerrero et al. 2018].

For edge detection, geometric approaches avoid using patches by considering geometric descriptors parameterizing each individual point [Demarsin et al. 2007; Weinmann et al. 2013]. Following this idea, Hackel et al. [2016] propose to train a random forest classifier taking as input geometric quantities obtained at multiple scales by linear regression in order to classify points belonging to edges.

In this paper, we introduce both a new way to individually parameterize points, together with a dedicated edge detection neural network classifier called *Point Cloud Edge Detection Network* (PCEDNet). Points are parameterized with a so-called *Scale-Space Matrix* (SSM) (Section 3.2) encoding extrinsic geometric properties of a locally reconstructed surface surrounding each point of the input point cloud at multiple scales. The use of this multi-scale parameterization allows us to propose a compact architecture (Section 3.3) based on a simple neural network enabling both its training in seconds or few minutes on small data sets, and the processing of 500 thousands of points per second on average with our current CPU implementation (Table 9). This fast training and the limited requirement on annotated data allow to

easily specialize our network to specific edge definitions, as illustrated in Figures 1-a and 1-b. It is fast enough to allow a user to interactively label small sub-parts of a point cloud and let our network annotate millions of points in seconds (Figure 1-c, Section 5.5).

The choice of our SSM values is validated by an ablation study (Section 5.1), and we evaluate the effectiveness of our network by comparing its speed and accuracy with existing geometric edge detection approaches, point-based processing networks, and two baselines: a Convolutional Neural Network (CNN) and a Fully Connected neural network (FC) (Section 3.4). Our results (Section 5) demonstrate the superiority of our PCEDNet over previous works, and illustrate its efficiency on a large variety of data, from CAD models to real world examples with tens of million of points (Figures 1-a and 20).

Current networks processing point clouds rely on very deep architectures in an end-to-end strategy. While the way our point parameterization is computed is not novel in geometry processing, the use of these parameters structured in our SSM as input of a network is new. Our proposition illustrates how a simple network exploiting these multi-scale geometric surface descriptors overpasses current approaches. We believe that its superiority in training and evaluation speed, scalability and resource requirements (computation and memory) makes it an example for the creation of lightweight point cloud processing solutions opening new perspectives regarding the system interactivity and adaptation to user's wishes. This is also a step forward to reach real-time point cloud processing with limited resources, which is becoming a very important challenge.

2 RELATED WORK

In this section, we first present the way unorganized point clouds are parameterized before being processed for geometric learning (Section 2.1). We introduce the different existing architectures for point-based machine learning and we discuss methods for edge detection from point clouds (Section 2.2). We then review geometric approaches (Section 2.3) dedicated to this topic.

2.1 Point cloud parameterization

Point clouds are most of the time defined as unordered and unstructured set of points sampling an unknown surface. When using neural networks on point clouds, a first challenge is to define a regular structure of the cloud that fits a network architecture, i.e. to *parameterize* the point cloud according to the network architecture. Several approaches have been proposed to tackle this challenge. A first class of approaches parameterizes unstructured point clouds in regular grids, e.g. using series of images taken from different viewpoints [Boulch et al. 2018, 2017; Kalogerakis et al. 2016; Su et al. 2015], or using voxel grids [Maturana and Scherer 2015; Qi et al. 2017a, 2016b; Wu et al. 2015; Zhou and Tuzel 2017]. The main limitation of these approaches is the cells memory requirement that limits their scalability to very large models especially when detecting thin structures and details, e.g. edges.

A second class of approaches processes each point and its neighborhood, so that the point coordinates are directly processed by the network. PointNet and its variants [Guerrero et al. 2018; Qi et al. 2016a, 2017b] use multi-layer perceptron (MLP) to consecutively sample and group point coordinates and build geometric features around a point. Several approaches have been proposed to extend convolution to 3D point clouds, using local spectral convolution [Wang et al. 2018], parameterized convolutional filters [Xu et al. 2018], transformed points [Li et al. 2018], sparse lattices [Su et al. 2018], adaptive kernels [Boulch 2019] and kernel point convolution [Thomas et al. 2019].

The strong benefit of point-based convolutions is to allow the design of networks whose first layers learn features at multiple scales directly from the point locations. On the other hand, the characterization of geometric structures relies

on the way convolution layers capture those features, only based on the local spatial organization of points. On real data, point sets also include sampling variation, noise, outliers and missing data that also have to be learned.

2.2 Network architectures

Most of the point-based geometry analysis neural networks are tailored for point cloud segmentation [Dai et al. 2017] and classification [Hackel et al. 2017; Zhirong Wu et al. 2015]. They follow the rational introduced by PointNet, where point coordinates are abstracted by successive layers, then reduced using max pooling for feature extraction and finally processed with MLP for the final decision. Such architectures aim at abstracting the input point cloud and estimating high level or semantic properties.

Some approaches also aim at processing point clouds according to their local geometric properties, e.g. normal estimation [Boulch and Marlet 2016]. PCPNet [Guerrero et al. 2018] learns local shape properties (e.g. normal vectors) directly from raw point clouds. Interestingly, this work suggests a multi-scale architecture where several networks process the surrounding of the analyzed point at increasing neighborhood size (one network per size). The features learned by the different networks are stacked to form a feature vector, and processed by a fully connected network to produce the final decision. Recently, the deep Learning Point Network architecture [Lê et al. 2020] improves the implementation of convolution-based point cloud processing networks such as PointNet, DGCNN [Wang et al. 2019] and SpiderNet [Zhao et al. 2020].

Overall, all these networks have been designed to extract semantic information from point clouds, which justify their both deep and large architectures. In our more geometric and specialized context, these architectures become unnecessarily complex while requiring long training and processing times.

2.3 Edge detection

Detecting edges in unstructured point clouds is usually cast as a sharp feature, a feature contour or a curve detection problem. It is often the first step of constrained surface reconstruction algorithms and over the years, many approaches have been proposed in this context. We refer the interested reader to the survey by Berger et al. [2017]. A standard approach is to compute at each point a geometric descriptor using the eigenstructure of the covariance matrix [Gumhold et al. 2001]. It can be a ratio between the eigenvalues, taking into account their evaluation at different scales [Pauly et al. 2003] or not [Xia and Wang 2017], or directly a curvature estimation [Lin et al. 2015; Nguyen et al. 2018]. The ratio between eigenvalues is considered as a more reliable parameter and it is, for instance, used in the CGA Library [CGAL [n.d.]] with a Delaunay-based feature estimation [Mérigot et al. 2011]. While well established, all these approaches suffer from a sensibility to noise and they perform at a given scale with a strong dependence to a decision threshold. The methods introduced by Pauly et al. [2003] and Bazazian et al. [2015] consider curvature ratio at different scales that reduces the dependence to the scale of analysis and the sensibility to noise, but they remain subject to a decision threshold.

Another family of methods relies on Moving Least Squares surface reconstruction [Demarsin et al. 2007; Ni et al. 2016; Weber et al. 2012]. Using this reconstruction, edge detection can be performed on a Gaussian map clustering computed in a local neighborhood [Weber et al. 2010]. Adaptive reconstruction kernels [Fleishman et al. 2005] can also be combined with polynomial fit [Daniels II et al. 2008]. Other approaches rely either on subspace detection and feature intersection computation [Fernandes and Oliveira 2012], on the mean-shift algorithm to select the farthest points from the centroid of their neighborhood [Ahmed et al. 2018], on the average of neighbors altitude over a local tangent plane [Li and Hashimoto 2017], or on the intersection of planes detected using RANSAC [Mitropoulou and

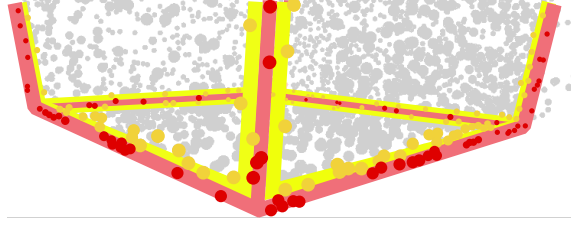


Fig. 2. Synthetic point cloud sampling a cube with sharp edges (red lines). Due to the sparse sampling and noise, only a few points lie on edges (red points). Detecting the edge surrounding (yellow points) improves the robustness to noise and sampling variation.

Georgopoulos 2019]. In other contexts, edges are defined as a specific type of lines on the surface. Lin et al. [2015] use RANSAC to spatially regularize the response of a sharp feature detector. Recently, Hackel et al. [2016] proposed a data-driven method where the points are classified and then structured using a graph-based approach. Extending local sharp feature detectors by a global analysis improves the robustness of the detection but limits the scalability, a critical aspect when processing large sets of points clouds defined by tens of million of points or more.

Finally, with an architecture based on PCPNet, ECNet [Yu et al. 2018] is a network consolidating edges after up-sampling the point cloud and detecting its edges. ECNet is thus a very deep network requiring important resources for training and processing points at inference time, while being limited in scalability by its up-sampling.

In this work, as suggested by Hackel et al. [2016], we propose to take advantage of the discrimination offered by geometric descriptors in a machine learning approach. We increase the robustness to noise and the adaptation to the different feature size/shape by the use of stable multi-scale descriptors including derivatives over scales. We then use these parameters together with a specifically designed neural network. By relying on this set of descriptive parameters, our network avoids the deep design of existing approaches by only requiring a very compact architecture that recursively combines the features learned at different analysis scales.

3 METHOD

3.1 Problem statement

Given a surface sampled by a point cloud, a sharp edge is commonly defined as a tangential discontinuity. Weber et al. [2010] define edges as sharp features (crests and valleys) between two meeting planes, as well as corners at the point of intersection between three or more planes. Hackel et al. [2016] call them "wire-frame contours", and define edges as linear features along which the orientation (normals) of the underlying surface exhibits an unusual discontinuity.

There are at least two main reasons why these definitions are restrictive and not really practical for the analysis of point clouds:

- (1) **Sparsity:** Points of acquired point clouds are unequally distributed over the object surfaces. Sharp edges are by nature very sparse, and it is very unlikely that the points of a point cloud actually sample the exact edge of the underlying surface as illustrated by the red points in Figure 2.
- (2) **Rounding:** Acquired point clouds are composed by points sampling real-world objects, on which edges are always more or less rounded/damaged (Figure 20). For instance, two facades of a building might be locally connected by a continuous curved surface considered as an edge at the scale of the building, which may be unlikely to be detected at lower scales such as the one of the bricks.

In order to handle these situations, we propose to classify points as **sharp-edge** when they lie on a sharp edge, and as **smooth-edge** when they are (1) near a sharp edge or (2) on a rounded edge. Other points are then labeled as **non-edge**. Depending on the application context and the artifacts found in the data, one might consider either one or the two edge classes in the results (we experimentally validate this proposition of two edge classes in Section 5.1). Considering that we do not have a universal and practical definition of an edge, we propose to learn the point-based classification of this feature from examples. In order to be robust to acquisition artifacts, sampling issues and edge roundness, we first reconstruct the surface described by the input points using a robust reconstruction algorithm, at multiple scales. We then compute geometric descriptors of the reconstructed surfaces, which are parameters to be processed by a machine learning algorithm (see Section 3.2). We show how this parameterization can be used with a common CNN and a fully connected neural network (Section 3.4), and we propose a dedicated architecture (Section 3.3) that outperforms these networks as well as previous edge classification approaches.

3.2 Scale-Space Matrix

Our approach is inspired by the Growing Least Squares (GLS) approach [Mellado et al. 2012], where the geometry surrounding a point is described by the differential properties of the surfaces reconstructed from neighborhoods of increasing size. We first present the basics of GLS, and then introduce the Scale-Space Matrix (SSM), which wraps in a regular structure the differential properties of the surfaces reconstructed at different scales.

The GLS extends the concept of Scale-Space analysis [Lindeberg 1993; Witkin 1987] to point-based shape analysis. The key idea is to detect pertinent geometric structures and scales as *stabilities* in scale-space. Stabilities are found when the magnitude of the derivatives of the surface is minimized when the scale varies. Due to its multi-scale nature, this approach disambiguates between noise and features, and detects geometric features defined at arbitrary scales. As such, points on a rounded and a sharp edge have discriminant descriptors and can be disambiguated during classification.

We denote $\mathcal{S}^t$ the *continuous surface* reconstructed at scale t , defined as the 0-isosurface of a scalar field $S^t(\mathbf{x}) : \mathbb{R}^3 \rightarrow \mathbb{R}$. We use the Algebraic Point Set Surfaces (APSS) [Guennebaud and Gross 2007] to reconstruct continuous surfaces from raw point clouds. This approach has been proven to be fast and stable at large scales [Guennebaud et al. 2008]. As many other previous work, the scale is controlled by varying the size of a neighborhood ball centered around the evaluation point.

In its original formulation, the pertinent scale extraction introduced by Mellado et al. [2012] combines several descriptors measuring the variation of local relief $\frac{\delta\tau(\mathbf{x},t)}{\delta t}$, normal orientation $\frac{\delta\eta(\mathbf{x},t)}{\delta t}$ and mean curvature $\frac{\delta\kappa(\mathbf{x},t)}{\delta t}$, where $\tau(\mathbf{x}, t) : \mathbb{R}^4 \rightarrow \mathbb{R}$, $\eta(\mathbf{x}, t) : \mathbb{R}^4 \rightarrow \mathbb{R}^3$ and $\kappa(\mathbf{x}, t) : \mathbb{R}^4 \rightarrow \mathbb{R}$ are scale-invariant properties of the surfaces $\mathcal{S}^t(\mathbf{x})$ (mathematical formulations are presented in Appendix A). They also use $\phi(\mathcal{S}^t(\mathbf{x}))$, the residuals of the fitting process, as confidence value.

In this work we propose to extend this idea further by measuring the surface variation in scale and space around each sample $\mathbf{p}_i$ of the input point cloud. We do not seek at defining an hand-crafted descriptor, but rather providing differential properties of the surface that are discriminant for edge detection. According to the GLS formalism, the parameters τ , η and κ are differentiable both in scale and space, which leads to a Jacobian matrix of 5×4 entries (see the description in Appendix A). By keeping only the quantities that are invariant by rigid transformations and not linearly dependent, we obtain the following feature vector X_i^t :

$$X_i^t = \begin{bmatrix} \tau_i^t & \kappa_i^t & k1_i^t & \frac{\delta\tau_i^t}{\delta t} & \frac{\delta\kappa_i^t}{\delta t} & \phi(S_{\mathbf{p}_i}^t) \end{bmatrix} \quad (1)$$

where $\tau_i^t = \tau(\mathbf{p}_i, t)$ and $\kappa_i^t = \kappa(\mathbf{p}_i, t)$. $k1_i^t$ measures the magnitude of the first principal curvature of the surface, and is computed from $\frac{\delta \eta_i^t}{\delta \mathbf{x}}$. According to our experiments, high values of τ , which measure the local relief, helps to disambiguate between rounded and sharp edges. The scale derivatives $\frac{\delta \tau_i^t}{\delta t}$ and $\frac{\delta \kappa_i^t}{\delta t}$ denote the stability of the reconstruction scale s_j .

The Scale-Space Matrix (SSM) defines a structured parameterization of the surfaces $\mathcal{S}^t$ described by the feature vectors X_i^t computed at N scales on each of the M points of the cloud. It is thus defined as follows:

$$SSM = \begin{bmatrix} X_1^1 & X_2^1 & X_3^1 & \dots & X_M^1 \\ X_1^2 & X_2^2 & X_3^2 & \dots & X_M^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_1^N & X_2^N & X_3^N & \dots & X_M^N \end{bmatrix}. \quad (2)$$

The minimum scale $s_{\min}$ is defined by the mean density of the point cloud, and the maximum scale $s_{\max}$ is 10% of the radius of the point cloud axis aligned bounding box (the effect of the variation of these values is presented in Section 5.6). According to previous work [Bronstein and Kokkinos 2010; Mellado et al. 2015], we use a logarithmic scale sampling to obtain scale-invariant feature vectors, such that

$$s_i = \left(\frac{s_{\max}}{s_{\min}} \right)^{\frac{i-1}{N-1}} * s_{\min}. \quad (3)$$

For all our experiments we use 16 scales distributed according to Equation 3. Even though we carefully selected the set of descriptors defining our SSM for their geometric meaning with respect to edge detection, we validate the optimality of this choice when parameterizing our neural network by an ablation study presented in Section 5.1.

3.3 Our network: PCEDNet

The architecture of our Point Cloud Edge Detection Network, denoted PCEDNet, is depicted in Figure 3. The input data is provided to the network as sixteen 6-dimensional vectors X_i^t per point, each vector corresponding to a scale. The sixteen scale vectors are concatenated by groups of two in order to form eight 12-dimensional vectors. More precisely, the first scale is grouped with the second one, the third one with the fourth one, and so on. The idea is to halve the number of scales iteratively until obtaining a single 12-dimensional vector as a final feature representation.

All the layers are fully-connected layers, also called dense layers (linear layer with biases), followed by a sigmoid activation function. For the first layer, each vector of size 12 is given to a dense layer comprised of 6 neurons. There are eight input vectors and each vector is fed to its own 6-neurons layer. The weights are not shared between these small layers, allowing to process the scales differently, as would do a convolution layer, but here, we combine scales by groups of two. The subsequent three layers perform similarly, but with 48, 24, 12 neurons, respectively.

The final 12-dimensional feature vector is given to a multi-layer perceptron (MLP) responsible for the classification. This MLP is composed of two 16-neuron dense+sigmoid layers followed by the output layer with 3 neurons and a softmax activation function. The total number of weights is about 2.1k, which makes our architecture very compact.

The goal of grouping different scales together is to observe the input shape at different scales in a simultaneous and more intricate way than without grouping them. We expect that this eases the simultaneous detection of higher-scale and sharp geometric properties of the input point clouds. Another reason is that such a representation helps the model to cope with noise in the point clouds.

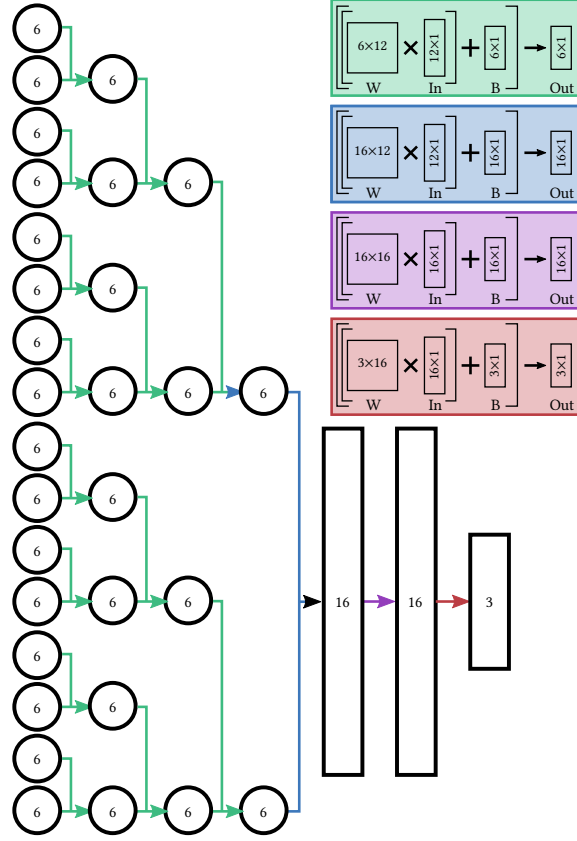


Fig. 3. Our PCEDNet architecture

The "tree structure" merging scales two by two iteratively can be seen as a variant of a grouped convolution operation. It preserves the high computing speed of keeping the scales separate while also mixing the scales layer after layer. It is expected to reduce the chance of being biased by a specific scale and the sensitivity to scale-dependent noise.

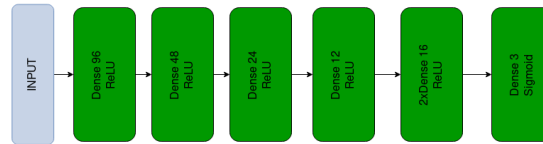


Fig. 4. Architecture of the FC baseline

3.4 Baseline models

The use of this new architecture is justified only if it performs better than more common choice of networks. We thus incorporate as baselines two networks in our evaluation:

- FC: A *Fully Connected* variant of PCEDNet where all scales are connected (Figure 4).

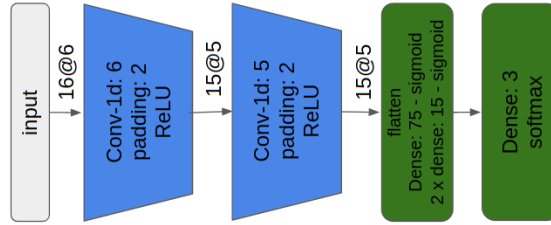


Fig. 5. Architecture of the CNN baseline

- CNN: A 1-d *Convolutional Neural Network* with a number of layers similar to our PCEDNet architecture (Figure 5).

FC. This architecture presented in Figure 4 allows us to measure the impact of the pairwise scale connection introduced in PCEDNet. FC and PCEDNet architectures differ by the four first layers: instead of consecutively combining scales by pairs, the FC baseline combines all the scales in unique dense layers while keeping the same reduction rate, i.e. 16-8-4-2 scales. We use the same number of neurons than PCEDNet to get comparable architectures. In total, the FC baseline is comprised of about 6663 weights (three times more than PCEDNet). The input data is provided to the network by concatenating the sixteen 6-dimensional vectors used by PCEDNet in a single 96-dimensional vector.

CNN. We chose a standard convolutional neural network architecture presented in Figure 5, composed of two blocks: a first block for representation learning with two 1D convolution layers, each followed by a ReLU activation function, and a second block dedicated to classification with three fully-connected layers and one 3D output layer. We tried a large number of variants and the one we present is the best we obtained by trials and errors. The two convolution layers are composed of 15 filters, with a kernel size of 6 and 5, respectively. Zero padding of size 2 was used to get outputs of shape 15×5 . The three dense layers are composed of 75, 15 and 15 neurons, respectively, followed by the output layer with 3 neurons. A sigmoid activation function is used after all the dense layers, except the output layer that uses a softmax non-linearity function. In total, CNN is composed of about 8.7k weights. The input data is also provided to the network as sixteen 6-dimensional vectors. Using the different scales as channels enables a potentially larger expressivity power to the model since each convolution filter uses different weights to combine the scales.

4 EXPERIMENTAL SETUP

4.1 Point cloud dataset

We measure the efficiency and adaptability of our network on three different datasets with ground truth for learning and evaluation: edges on point clouds with acquisition artifacts (Default), sharp edges on CAD models (ABC) and annotated curves on challenging shapes (SHREC). Each dataset is split in three sets: training set (denoted T, used for training), validation set (denoted V, used for learning to monitor accuracy) and evaluation set (denoted E). Visual evaluations are also conducted on a set of acquired models. Point clouds with classification results are shown in the website accompanying the submission.

In addition to annotated learning sets, we also show in Section 5.5 how PCEDNet can learn from small set of data annotated interactively by a user and classify point clouds without requiring additional predefined training data.

Default dataset. We design this dataset to emulate geometric structures regularly found in acquired point clouds. It is as small as possible, in order to demonstrate that few annotated data training our network in a short time (see

timings in Table 2) are enough for an effective detection. The Default dataset is composed of synthetic data containing edges of different shapes illustrated in Figure 6. We also included displacement noise (Figure 6-right column), with several objects characterized by different densities and shapes. We defined the validation set by selecting a random subset within the training set with an equal number of points across the three classes (1k per class 3k in total). We also created an evaluation set with specific features to better evaluate the networks against noise and sharp angles. These point clouds, not used for training, are taken from the testing set introduced by Bazazian et al. [2015] to evaluate the algorithm Covariance Analysis (denoted CA in the following). The noise used at the training and evaluation stages has been added on the [Cube](#), [Cone](#), [Fandisk](#) and [2-cubes](#) models by applying a random motion on the points following a Gaussian distribution with standard deviation denoted σ . Table 1 presents quantitative details (including the values used for σ), and the point clouds are shown in Figures 6, 7 and in the joined website.

ABC dataset. We use the ABC dataset [Koch et al. 2019] to evaluate the performance of our network on the detection of sharp edges in CAD models. We use the chunk 000, which contains 7167 models represented as OBJ files. We generate

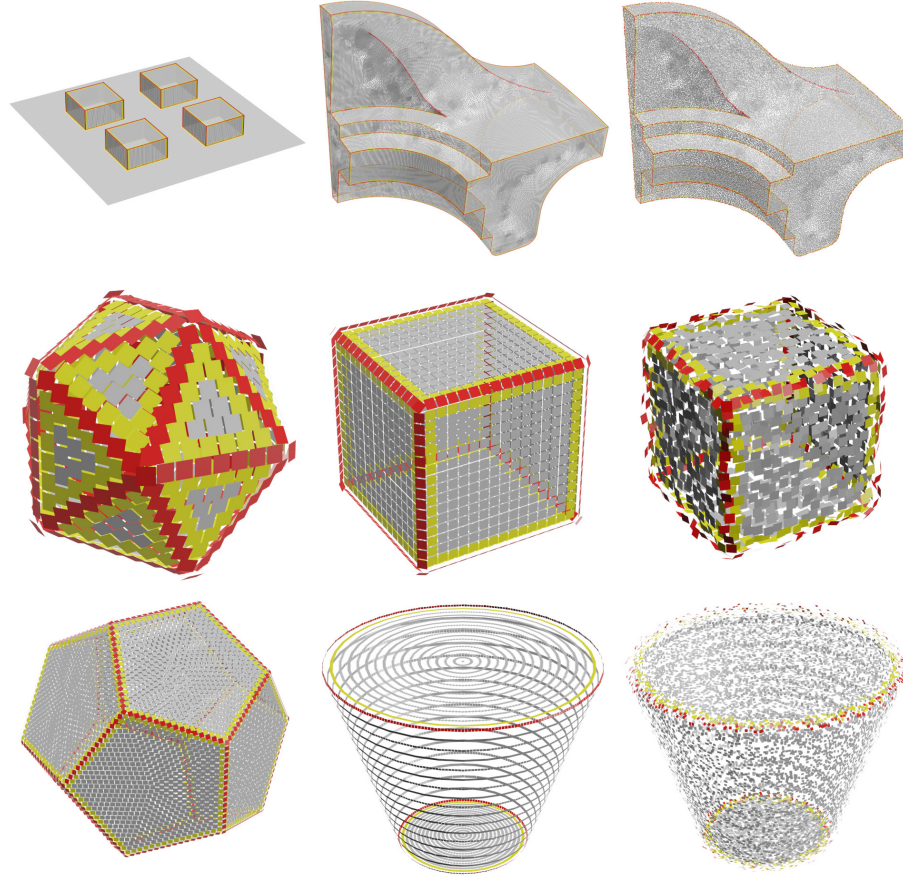


Fig. 6. Training set of the dataset Default, with sharp edges points in red, and smooth edges points in yellow.

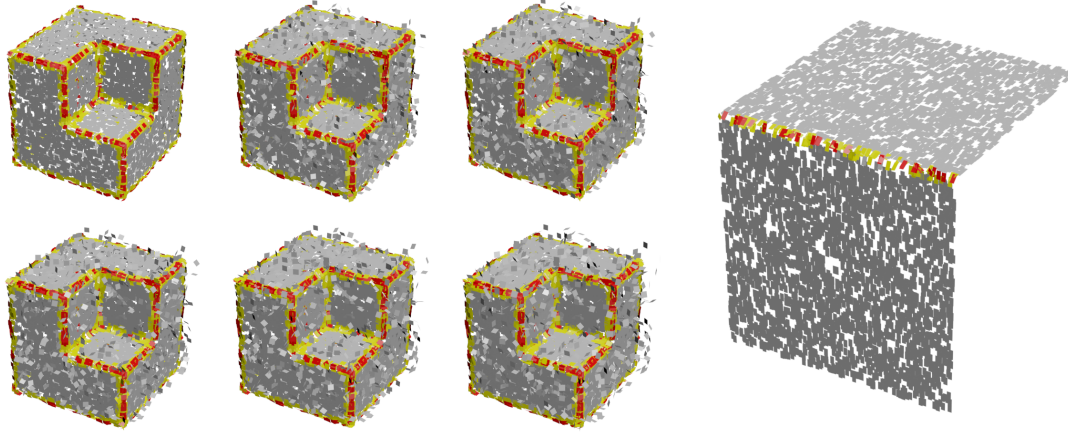


Fig. 7. Evaluation set of the dataset Default. Left: 2-cubes, with increasing Gaussian noise (σ ranging between 0 and 0.14 units, cube edge length 1). Right: Angle (90 degrees).

Dataset	Model	Usage	#k points	% points/class			Noise (σ)
				Edge	S-Edge	Other	
Default	Cube	T, V	1.5	12.2	21.8	65.9	0-0.1
	Icosahedron	T, V	0.6	34.6	46.7	18.6	-
	Cone	T, V	7.7	6.1	11.7	82.2	0-0.1
	Dodecahedron	T, V	12	3.5	7.7	88.7	-
	Fandisk	T, V	106.5	5.5	5	89.4	0-0.1
	4-cubes	T, V	43.9	6.8	6.6	86.5	-
	2-cubes	E	7.2	6	17.3	76.6	0 - 0.01 0.02 - 0.03 0.12 - 0.14
	Angle	E	6	0.6	1.6	97.8	-
Default (total)		T	287.9	9	11	80	-
		V	3	33.3	33.3	33.3	-
		E	55	4.9	14.54	80.56	-
SHREC		T	89.4	13.98	-	86.02	-
		V	94.4	8.68	-	91.32	-
		E	654.7	10.57	-	89.43	-
ABC		T	3212.4	4.66	-	95.34	-
		V	690	5.79	-	94.21	-
		E	312314	5.52	-	94.48	-

Table 1. Statistics of the datasets used for training (T), validation (V) and evaluation (E). The Edge column gives the percentage of points of the class sharp-edge, the S-Edge, the one of the class smooth-edge and Other is for the non-edge class.

the point clouds by exporting the vertices and the normal vectors of the meshes. The ground truth classification is produced using the vertices associated to a sharp feature in the feature files. A notable difference with the Default dataset is that no ground truth information is provided for the smooth-edge label. Only sharp edges are considered and other smoother features are thus labeled as non-edge. We define the training and evaluation sets by randomly selecting 200 and 50 models respectively (see the model list in the joined website).

SHREC dataset. We use the dataset produced for feature curve extraction by Thompson et al. [2019] in order to evaluate the performance of our network on challenging data annotated by humans. As for ABC, we consider the vertices and normal vectors of the given meshes, and mark the annotated vertices as edge vertices. Similarly, we define the training and evaluation sets by randomly selecting models, e.g., (M5, M6 and M14) and (M2, M11) respectively. This

procedure is not ideal as these models exhibit very heterogeneous edge shapes, but we found it fairer than randomly sampling the point clouds.

Acquired point clouds. We also perform visual evaluations on 9 acquired point clouds whose number of vertices are reported in Table 9. **Loudun 1** and **Loudun 35** are down-sampled versions (of respectively 1 and 35 millions vertices) of a photogrammetric acquisition of the Square Tower of Loudun (France). We used **Euler**, **Empire** and **Lans** as provided by Monszpart et al. [2015], **Pisa Cathedral** as provided by Mellado et al. [2015], **Munich** as provided by Hackel et al. [2016], and we downloaded **Church** and **Train Station** from Sketchfab¹.

Normal estimation. The normals used for the GLS computation are either directly those estimated with the acquisition technique (e.g. photogrammetry, laser scanner), which are actually provided for most current acquisition devices, or those computed automatically from the point samples (we used Meshlab [Cignoni et al. 2008] to estimate normals on **Default** dataset and on **Euler**, **Lans**, **Church** and **Train Station**). We did not encounter any difficulty related to normal estimation. Eventually, oriented normals may be avoided and replaced by unoriented normals [Chen et al. 2013a], which could be easily estimated using local fitting.

4.2 Networks training

Implementation details. We implemented PCEDNet in C++ and ran our experiments on a 40-cores Intel Xeon-E5-2640v4 2.40GHz, with 128GB RAM. We use the Ponca library [Mellado et al. 2020] for surface fitting and derivative computation. The network modeling and evaluation for PCEDNet and FC is implemented in our own prototype using Eigen [Guennebaud et al. 2010] for linear algebra. The baseline CNN is implemented, trained and evaluated using Pytorch.

Categorical cross-entropy is used as objective function for both the baseline architectures and PCEDNet. On each dataset, CNN, FC and PCEDNet are trained for 200, 200 and 40 epochs respectively, all reaching 98% accuracy on the validation sets. Weights are initialized randomly using the Glorot and Bengio [2010] method. For the three architectures, learning rate is set to 0.01, momentum to 0.9, with batch size of 100 points.

Training. As illustrated in Table 1, the three training sets contain mostly non-edge surfaces. The small number of sharp and smooth edge samples (4-14% of the points) implies that we are in presence of a highly unbalanced training set biased towards the non-edge class. We handle this issue by generating balanced batches of points during training. We recorded training curves for PCEDNet on dataset **Default** (see Figure 8 and Table 5). Training usually takes a couple of minutes for PCEDNet, a dozen for the baseline FC, and more than one hour for CNN.

5 RESULTS

In this Section, we first validate our choice of input parameters with an ablation study (Section 5.1). We then compare in Section 5.3 our network with our baseline (i.e. CNN and FC), with ECNet [Yu et al. 2018] and PCPNet [Guerrero et al. 2018] and two geometric feature detection methods, i.e. the covariance analysis method proposed by Bazazian et al. [2015] (CA) and the Feature Edge Estimation (FEE) implemented in the CGAL Library [CGAL [n.d.]; Mérigot et al. 2011]. For clarity, we denote A(D) the approach A trained on dataset D, e.g., PCEDNet trained on **Default** is denoted PCEDNet (**Default**). All of the Figures of the next sections are available in full resolution on the joined website homepage, with left/right interactive comparisons between the methods. Results of the quantitative experiments on each dataset are

¹**Church**: <https://sketchfab.com/3d-models/christ-church-and-dublin-city-council-b5f6bce8ebc44a3b4bbb6b0fef067b3>. **Train Station**: <https://sketchfab.com/3d-models/station-rer-6c636ca4793345e8ae12beb97b7d6359>

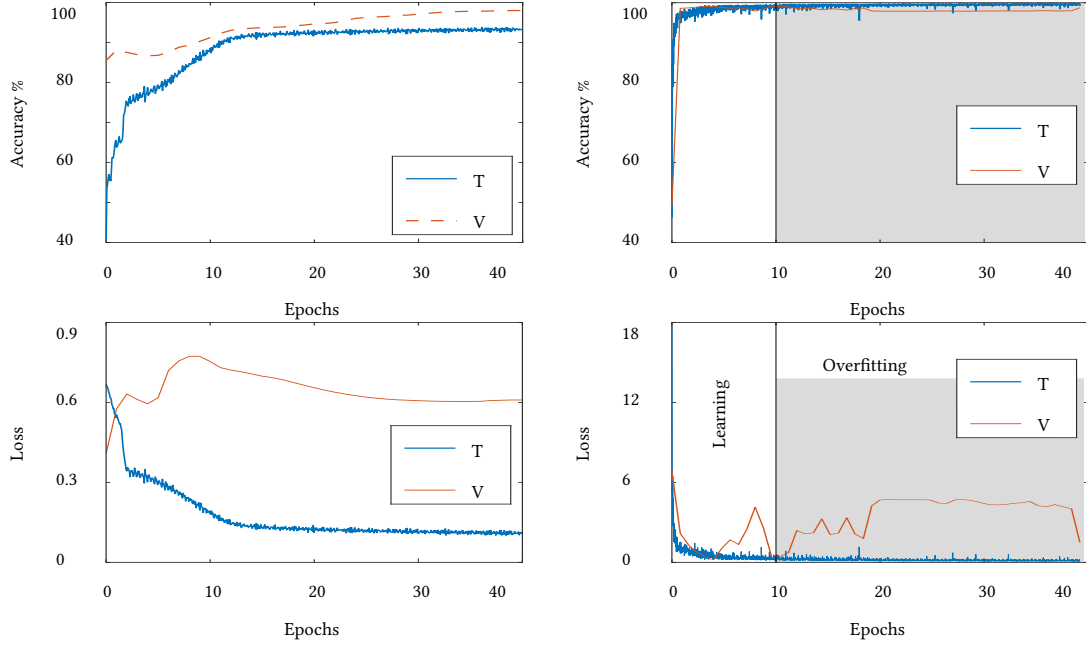


Fig. 8. PCEDNet: learning curves measured on Training (T) and Validation (V) sets on the (left) Default and (right) ABC. For the latter, learning stops automatically at epoch 10, when loss and accuracy stop to be improved.

Method	GLS	Training	Total
PCEDNet (Default)	19.32 s	2:52 m	3:11 m
PCEDNet-2C (ABC)	2:11 m	20:00 m	22:11 m
PCEDNet-2C (SHREC)	4 s	28.09 s	32.09 s
FC (Default)	19.32 s	13:58 m	14:17 m
FC-2C (ABC)	2:11 m	2:01:05 h	2:03:16 h
FC-2C (SHREC)	4 s	10:03 m	10:07 m
CNN (Default)	19.32 s	1:19:08 h	1:19:27 h
CNN-2C (ABC)	2:11 m	9:00:00 h	9:02:11 h
CNN-2C (SHREC)	4 s	26:01 m	26:05 m

Table 2. Training times of our networks on the different datasets.

documented in dedicated webpages presenting interactive distribution plots, histograms, tables, and a 3D point cloud viewer.

Comparison metrics. We compare positive and negative matches of the classifications w.r.t. ground truth by measuring True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). To do so, we consider the following metrics: Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), and Accuracy, whose formulations are given in Appendix B. Note that F1 ignores the True Negatives and thus is misleading for unbalanced classes, which is our case in general, i.e. the number of TP edge points is in general very small in comparison to the TN non-edge points. It is however reported for comparison as F1 is commonly used in similar contexts. In our case, MCC is a more representative score for evaluation.

		2-cubes (σ)						Angle
		0	0.01	0.02	0.03	0.12	0.14	
All GLS derivatives (28 parameters)	P	0.529	0.305	0.348	0.413	0.310	0.340	0.327
	R	0.415	0.424	0.454	0.481	0.427	0.45	0.5
	F1	0.465	0.355	0.394	0.445	0.360	0.387	0.396
	MCC	0.435	0.310	0.353	0.407	0.315	0.345	0.400
Invariant to rigid transformations (7 parameters)	P	0.983	0.839	0.866	0.882	0.845	0.853	0.871
	R	0.823	0.904	0.921	0.912	0.904	0.919	0.984
	F1	0.897	0.871	0.893	0.897	0.874	0.885	0.925
	MCC	0.870	0.828	0.858	0.864	0.832	0.848	0.924
Our configuration (6 parameters)	P	0.966	0.807	0.832	0.868	0.817	0.826	0.724
	R	0.897	0.960	0.970	0.934	0.961	0.964	0.984
	F1	0.931	0.877	0.896	0.901	0.884	0.890	0.835
	MCC	0.908	0.839	0.864	0.869	0.847	0.856	0.840
Remove scale (4 parameters)	P	0.360	0.217	0.250	0.265	0.217	0.233	0.428
	R	0.340	0.489	0.513	0.696	0.475	0.495	0.416
	F1	0.350	0.301	0.337	0.385	0.298	0.317	0.423
	MCC	0.305	0.260	0.299	0.373	0.256	0.277	0.419
Remove curvature (3 parameters)	P	0.173	0.103	0.115	0.355	0.105	0.109	0.242
	R	0.292	0.290	0.277	0.783	0.290	0.286	0.222
	F1	0.217	0.152	0.163	0.489	0.155	0.158	0.232
	MCC	0.152	0.079	0.094	0.484	0.084	0.087	0.227

Table 3. Precision, recall, F1 and MCC computed on the 2-cubes (with a Gaussian noise generated with different value of σ) and Angle models of the Default evaluation set (see Table 1) for the different parameterization of PCEDNet.

Comparison of classifications with two and three classes. As previously stated, PCEDNet outputs three classes corresponding to sharp-edges, smooth-edges and non-edges. However if edges are defined as sharp features only (i.e. the ABC dataset), results from the smooth-edge class does not bring significant quantitative information and only the sharp-edge class is of interest. In that case, we consider the sharp-edge as the unique positive class, and merge the smooth-edge and non-edge classes as the negative class. When a more fuzzier definition is used for edges, as for the SHREC dataset where both rounded and sharp edges co-exists, we present additional results where the positive class is defined either as sharp edge only, or, as the union of sharp-edges and smooth-edges classes. Accordingly, three-classes approaches are trained on two-classes datasets as if no vertex is labelled as smooth-edge, but only has sharp-edge or non-edge.

5.1 Ablation study

In this Section, we validate both the choice of input parameters and the number of output classes (i.e two or three) of PCEDNet. Quantitative results are given respectively in Tables 3 and 4.

SSM. Our Scale-Space Matrix is composed of 6 parameters computed by differentiating the GLS implicit surface both in scale and space. In order to measure the relevance of our parameterization, we tested four alternative sets of parameters, ranging from 28 to 3 parameters per scale. For each scenario, the PCEDNet architecture is modified as follows: the number of weights of the four first layers is set according to the number of input parameters, as well as the connection between the fourth and fifth layers. We define the different parameter sets as follows:

- 28 parameters: taking all the derivatives of the GLS descriptor in scale and space,
- 7 parameters: keeping only the derivatives that are invariant to rigid transformations (rotation, translation and scale), leading to $\left[\tau_i^t \quad \kappa_i^t \quad k1_i^t \quad k2_i^t \quad \frac{\delta \tau_i^t}{\delta t} \quad \frac{\delta \kappa_i^t}{\delta t} \quad \phi(S_{p_i}^t) \right]$,
- 6 parameters (selected PCEDNet input): removing $k2$, which is linearly dependent to $k1$ and κ ,
- 4 parameters: removing scale information from PCEDNet input, leading to $\left[\tau_i^t \quad \kappa_i^t \quad k1_i^t \quad \phi(S_{p_i}^t) \right]$
- 3 parameters: removing curvature information from PCEDNet input, leading to $\left[\tau_i^t \quad \frac{\delta \tau_i^t}{\delta t} \quad \phi(S_{p_i}^t) \right]$.

		2-cubes (σ)						Angle
		0	0.01	0.02	0.03	0.12	0.14	
PCEDNet-2C (Default)	P	0.576	0.298	0.366	0.364	0.308	0.330	0.435
	R	0.564	0.610	0.652	0.689	0.611	0.614	0.278
	F1	0.570	0.400	0.469	0.477	0.410	0.430	0.339
	MCC	0.539	0.374	0.445	0.458	0.383	0.402	0.344
PCEDNet (Default) (Ours)	P	0.966	0.807	0.832	0.868	0.817	0.826	0.724
	R	0.897	0.960	0.970	0.934	0.961	0.964	0.984
	F1	0.931	0.877	0.896	0.901	0.884	0.890	0.835
	MCC	0.908	0.839	0.864	0.869	0.847	0.856	0.840

Table 4. Precision, Recall, F1 and MCC computed on the 2-cubes (with different Gaussian noise) and Angle models of the Default evaluation set (presented in Table 1) for PCEDNet and its two-classes implementation PCEDNet-2C. As we can see, the addition of the third class improves the classification quality of the sharp-edge class.

We trained these five parameter configurations on Default and reported in Table 3 the Precision, Recall and F1 scores when applied on the evaluation set. As we compare 3-classes approaches on a 3-classes dataset in this experiment, we sum-up TP and FP for both the sharp-edge and smooth-edge labels, and use non-edge for negatives. Our choice of 6 parameters is validated as it always has the higher Recall, F1 and MCC, while providing a good precision in comparison with the other sets of parameters.

Number of output classes. We measure the impact of the smooth-edge class on the quality of the sharp-edge classification by implementing a version, denoted PCEDNet-2C, in which the decision layers return scores for 2 classes instead of 3. We trained PCEDNet-2C on the Default dataset by considering points labelled as sharp-edge for one class and as the union of non-edge and smooth-edge for the other class. We report in Table 4 the scores obtained by PCEDNet and PCEDNet-2C on the evaluation set. We can see that the addition of the third class allows PCEDNet to obtain higher scores than PCEDNet-2C, for all the metrics. Note that one class could have been the union of sharp and smooth edges and the other the non-edges. This increases the false positive rate and leads to the same best parameterization, with overall lower performance.

5.2 Training and classification times

In this section we compare the learning and evaluation speed of our specialized approach to more versatile networks based on PointNet [Qi et al. 2016a], the state of the art solution for point-based learning and semantic shape analysis. Among the different possibilities, we selected ECNet [Yu et al. 2018] and PCPNet [Guerrero et al. 2018], as they can be easily adapted to our more geometric and focused problem.

Experimental setup for compared approaches. For PCPNet, we run a specialization training in order to adapt its original output from point normals estimation to point classification. We removed the output normalization from their architecture, and trained the last layers of the network (using the default hyperparameters provided by the authors) using our data (400 epochs on Default, and 50 epochs on ABC). This allows us to take advantage of PCPNet original training for the first layers. For ECNet, we directly use the pre-trained version provided by the authors. In the nutshell, this approach oversample an input point cloud, and label each generated point as edge or non-edge. We retrieve the classification of the input point cloud by assigning to each input point the label of the closest output sample. Both PCPNet and ECNet approaches require more computation power and memory than provided by our 40-cores Intel Xeon-E5 to handle large data sets as ABC. For training and evaluating these networks, we thus used a NVIDIA Quadro RTX 6000 with 24GB of G-RAM. This is reminded by a * in the text when we report timings.

Method	PCPNet	PCEDNet
Default	40:00 m *	3:11 m
ABC	19:00:00 h *	22:11 m

Table 5. PCPNet training times on the Default and ABC datasets. We also remind the PCEDNet training times for comparisons.

Training. We trained PCPNet with three classes on our Default dataset (denoted PCPNet (Default)) and with two classes on ABC (denoted PCPNet (ABC)). As shown by the loss plot in Figure 9-left, training of the deep architecture of PCPNet converge to relatively high loss on our Default training set. Also, despite several attempts, PCPNet couldn't stabilise on SHREC due to the high variability of the annotations. Training on a larger dataset such as ABC (see the loss plot in Figure 9-right) is better adapted and enables the convergence of PCPNet training with low loss. Regarding the timings, PCPNet requires significantly longer training than our approach (more than 500 times slower on ABC), as reported in Table 5.

Classification. In addition to ECNet and PCPNet, we compare our approach with CA [Bazazian et al. 2015] (for all our experiments, we used 10 neighbors and threshold=0.65, except for Munich for which we used 20 neighbors to handle sparse sampling), FEE [Mérigot et al. 2011] (we specifically adjusted parameters for each dataset), our baselines CNN and FC. We report in Figure 10 the evolution of the classification timings (in logarithmic scale) when increasing the point cloud size. We observe for PCEDNet, FC and CNN that scale-space calculation (which can be done in pre-process) requires more time than the classification itself. It also illustrates how fast our compact network architecture is, compared to more complex and computationally intensive architectures as PCPNet and ECNet. Finally, PCPNet and ECNet require more than 24 GB G-RAM to handle large point clouds and we thus could not provide the timings for the classification of our larger models by these networks.

5.3 Quantitative evaluation

We now compare the classification produced by the aforementioned approaches with ground truth classification on datasets Default, ABC and SHREC.

Default dataset. Results are reported in Table 6 and illustrated in both Figure 12 and the accompanying website. Both CNN and FC are strong baselines getting significantly higher MCC scores than most methods from previous work. PCPNet exhibits very different behaviors depending on the training set. For instance, PCPNet (ABC) cannot disambiguate

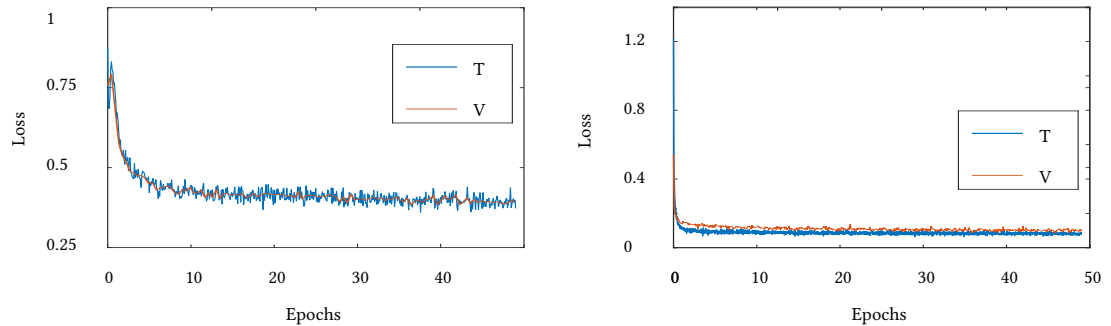


Fig. 9. PCPNet: learning curves measured on Training (T) and Validation (V) sets on the (left) Default and (right) ABC datasets.

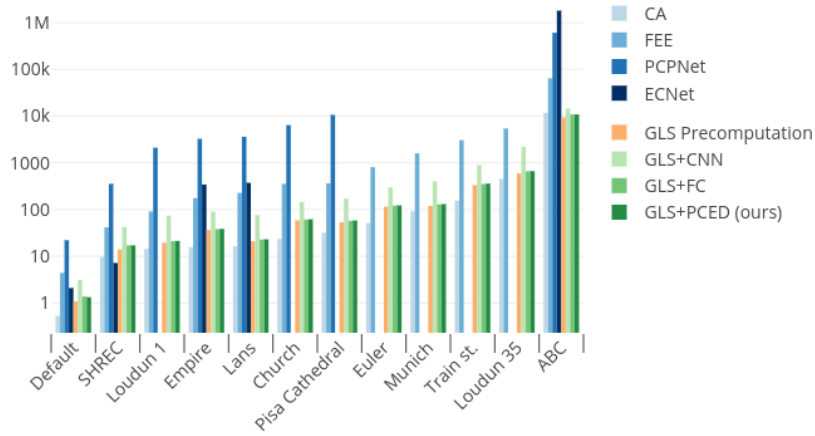


Fig. 10. Time (in seconds) required by the approaches presented in Table 9 to classify different models.

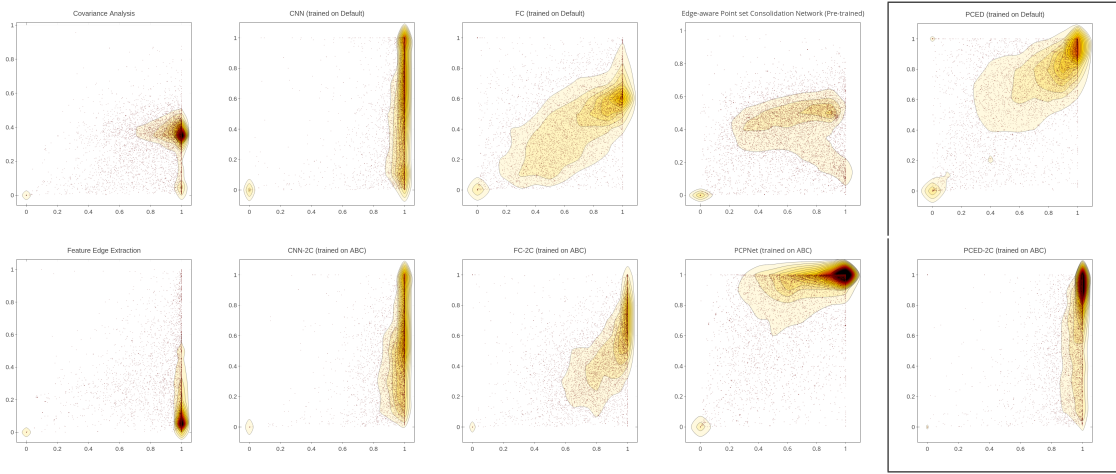


Fig. 11. Distribution of the Precision/Recall scores display as scatter plot (each point cloud is a sample) and its associated density function for the ABC dataset. Interactive plots are provided in the joined website.

between sampling variation and edges (point clouds in ABC have very regular sampling), which leads to very high false-detection rates. PCPNet (Default) does not exhibits this issue, however it shows very limited detection for sharp

Method	Precision	Recall	MCC	F1	Accuracy
CA	0.490	0.880	0.506	0.628	0.752
FEE	0.341	0.814	0.471	0.480	0.879
PCPNet (Default)	0.722	0.198	0.301	0.310	0.789
PCPNet (ABC)	0.081	0.399	0.221	0.136	0.298
ECNet	1.000	0.457	0.656	0.620	0.960
CNN (Default)	0.546	0.955	0.623	0.694	0.807
FC (Default)	0.618	0.958	0.682	0.753	0.849
PCEDNet (Default)	0.826	0.952	0.857	0.890	0.946
PCEDNet-2C (ABC)	0.224	0.598	0.286	0.313	0.850

Table 6. Quantitative evaluation on Default: median scores (see score of the other approaches in the accompanying website).

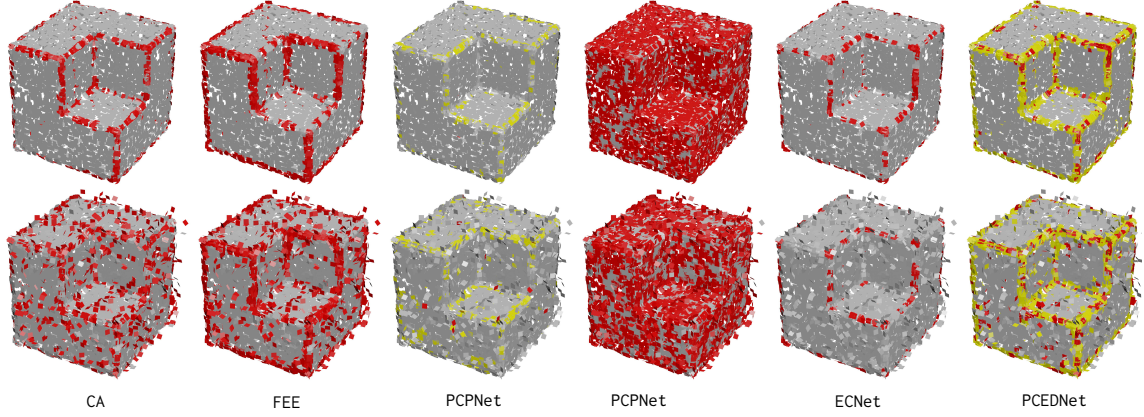


Fig. 12. Classification on Default, model 2-cubes: $\sigma = 0$ (top) and 0.14 (bottom). See results of the other approaches in the accompanying website.

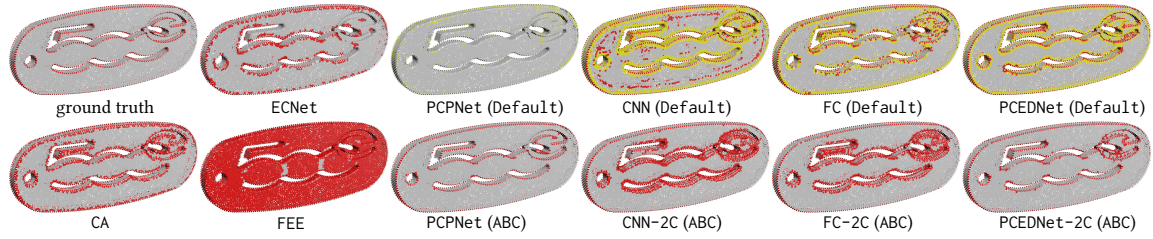


Fig. 13. Model 7029 of the ABC dataset.

edges. ECNet produces very precise classifications even on noisy models, but overall misses to classify 50% of the points labeled as edges in ground truth (high precision and low recall). Regarding single-scale fitting-based approaches (i.e. CA and FEE), both approaches fail at handling outliers (for FEE, we used the following parameters: $r = 0.025$, $R = 0.05$ and $th = 0.16$). PCEDNet (Default) produces the best results on this dataset, getting significantly higher indicators than other approaches. Also, PCEDNet-2C (ABC) shows better adaptation than PCPNet (ABC), with higher scores for all indicators.

ABC dataset. Due to the large size of ABC (7166 models) we present in Figure 11 (and in the accompanying website) the results as a precision/recall scatter plots, which provide a more readable overall view of the performance of the different approaches. For each approach, we plot each 3D model as a point sample, and display the resulting density

Method	Precision	Recall	MCC	F1	Accuracy
CA	0.348	0.944	0.520	0.504	0.881
FEE	0.135	1.000	0.062	0.235	0.278
ECNet	0.425	0.648	0.423	0.460	0.910
PCPNet (ABC)	0.954	0.756	0.797	0.807	0.979
CNN (Default)	0.530	0.995	0.648	0.689	0.922
CNN-2C (ABC)	0.507	0.983	0.646	0.662	0.928
FC (Default)	0.452	0.679	0.469	0.513	0.921
FC-2C (ABC)	0.470	0.871	0.555	0.581	0.920
PCEDNet (Default)	0.746	0.745	0.688	0.713	0.966
PCEDNet-2C (ABC)	0.735	0.984	0.808	0.822	0.970
PCEDNet-2C (Default)	0.662	0.936	0.708	0.730	0.958

Table 7. Quantitative evaluation on ABC: median scores.

maps as 2D-contour maps. We use the Hot colormap, with density values ranging from 50 (light yellow) to 1000 (dark red). A perfect classification result would lead to a Dirac distribution centered at location (1,1) and with magnitude 7166. Most of the analysed approaches are producing classifications with high recall, but differ by their capacity to reach high precision. Table 7 shows the median statistical scores obtained by each method on the whole dataset. Single-scale fitting-based approaches, e.g., CA and FEE (we use $r = 0.4$, $R = 0.8$ and $th = 0.16$ for this dataset) exhibit very high recall but low precision (lower than 0.4) with the classification of a lot of FP. As shown in supplementary materials, these approaches produce good results for very clean and simple geometries, but fail at analyzing thin objects (i.e. neighborhood might include two pieces of opposite surfaces, see FEE in Figure 13) and other intricate shapes. CNN follows a similar pattern, but is able to produce better classifications with high precision ($MCC \approx 0.65$). FC produces results with lower quality ($MCC < 0.55$) and higher dependency to the training set. Both FC (Default) and FC-2C (ABC) are however competitive compared to state of the art methods. Overall, the quality of ECNet results (in term of MCC, F1 and Accuracy) is overall better than fitting-based approaches, but lower than our baselines. All the variants of our PCEDNet produce better results, with MCC scores above 0.8 for PCEDNet-2C (ABC). Despite the large difference between the training sets of Default and ABC, our approach PCEDNet (Default) produces classifications with better MCC than competitors ($MCC = 0.688$), but at the cost of a recall loss. As shown in the joined website, the classifications produced by both PCEDNet (Default) and PCEDNet-2C (ABC) remain visually convincing despite quantitative differences against the ground truth. A notable exception to the global trend high-recall/variable-precision is PCPNet (ABC), which exhibit higher precision/lower recall than any other approach. It also reaches comparable scores than our approach (e.g. MCC, F1, Accuracy), but visual inspection reveals that PCPNet (ABC) tends to miss some edges entirely (lower recall), while our approach finds relatively thicker edges (lower precision). Also, PCPNet (ABC) requires 3 days to process the entire dataset (instead of 3 hours for PCEDNet-2C (ABC)).

SHREC dataset. This dataset has been originally designed to evaluate curve detection algorithms on organic and relatively smooth objects with a comparison to human labelling. In addition, some objects have strong semantics (e.g. human face), and we observe that the ground-truth classification seems to take into account this semantic rather than strictly respecting geometric features. This makes this SHREC dataset very challenging to label, as illustrated in Table 8

Method	Prec.	Recall	MCC	F1	Accuracy
CA	0.434	0.449	0.390	0.442	0.876
FEE	0.191	0.527	0.151	0.278	0.727
PCPNet (Default)	0.000	0.000	0.000	0.009	0.893
PCPNet (ABC)	0.399	0.250	0.211	0.310	0.943
ECNet	0.365	0.503	0.341	0.397	0.845
CNN (Default)	0.468	0.928	0.570	0.611	0.911
CNN (Default)~	0.299	0.945	0.429	0.446	0.802
CNN-2C (ABC)	0.271	0.496	0.234	0.315	0.818
CNN-2C (SHREC)	0.207	0.881	0.202	0.248	0.622
FC (Default)	0.392	0.538	0.391	0.455	0.880
FC (Default)~	0.313	0.909	0.428	0.461	0.793
FC-2C (ABC)	0.389	0.693	0.369	0.438	0.846
FC-2C (SHREC)	0.406	0.715	0.392	0.480	0.849
PCEDNet (Default)	0.495	0.377	0.344	0.437	0.916
PCEDNet (Default)~	0.349	0.898	0.444	0.489	0.814
PCEDNet-2C (Default)	0.462	0.623	0.455	0.510	0.868
PCEDNet-2C (ABC)	0.479	0.621	0.394	0.561	0.901
PCEDNet-2C (SHREC)	0.441	0.872	0.426	0.522	0.874

Table 8. Quantitative evaluation on SHREC: median scores. For 3-classes methods marked with ~, we compare both the smooth and sharp edges classes with the ground truth, i.e. Positives=Sharp+Smooth.

Dataset	#obj	#vert.	CA	FEE	PCPNet	EC	GLS	CNN (total)	FC (total)	PCEDNet (total)
Loudun 1	1	1M	14.30 s	1:30 m	35:00 m *	-	19.30 s	0:54 (1:13) m	1.80 (21.10) s	2.10 (21.40) s
Empire	1	1.2M	15.70 s	2:55 m	54:22 m *	5:43 m *	36.40 s	0:53 (1:29) m	1.80 (38.20) s	2.10 (38.50) s
Lans	1	1.23M	16.40 s	3:46 m	1:00:08 h *	6:13 m *	21.00 s	0:55 (1:16) m	1.80 (22.80) s	2.10 (23.10) s
Church	1	1.9M	23.40 s	5:53 m	1:46:40 h *	-	58.40 s	1:26 (2:24) m	0:02 (1:01) m	0:03 (1:01) m
Pisa Cathedral	1	2.5M	31.80 s	6:03 m	2:56:40 h *	-	53.60 s	1:57 (2:50) m	3.90 (57.50) s	4.70 (58.30) s
Euler	1	3.9M	51.20 s	13:22 m	-	-	1:55 m	3:00 (4:55) m	0:06 (2:01) m	0:07 (2:02) m
Munich	1	6M	1:31 m	26:33 m	-	-	1:59 m	4:41 (6:41) m	0:09 (2:09) m	0:11 (2:10) m
Train St.	1	12.45M	2:35 m	50:44 m	-	-	5:31 m	9:17 (14:49) m	0:19 (5:50) m	0:25 (5:57) m
Loudun 35	1	35M	7:29 m	1:30:25 h	-	-	9:52 m	26:38 (36:30) m	1:06 (10:59) m	1:09 (11:02) m
Default	8	55k	0.53 s	4.41 s	22.11 s *	2.09 s *	1.08 s	2.03 (3.11) s	0.30 (1.38) s	0.25 (1.33) s
SHREC	15	654k	9.70 s	41.47 s	5:54 m *	7.20 s *	14 s	28.58 (42.58) s	3.10 (17.10) s	3.10 (17.10) s
ABC	7167	312.3M	3:15:00 h	17:50:00 h	7 d *	20 d *	2:35:00 h	1:25:00 (4:00:00) h	0:25:40 (3:00:40) h	0:25:30 (3:00:30) h

Table 9. Timing comparison for classification, where (s) stands for seconds, (m) for minutes, (h) for hours, and (d) for days. For datasets (e.g., Default, SHREC and ABC) we report the time needed to process all the models. The column *GLS* corresponds to the precomputation of the GLS descriptors. For columns CNN, FC and PCED, we report first the classification time, followed in brackets by the total_time = GLS+reported_time. Timings marked with * have been obtained using dedicated hardware (NVIDIA RTX 6000).

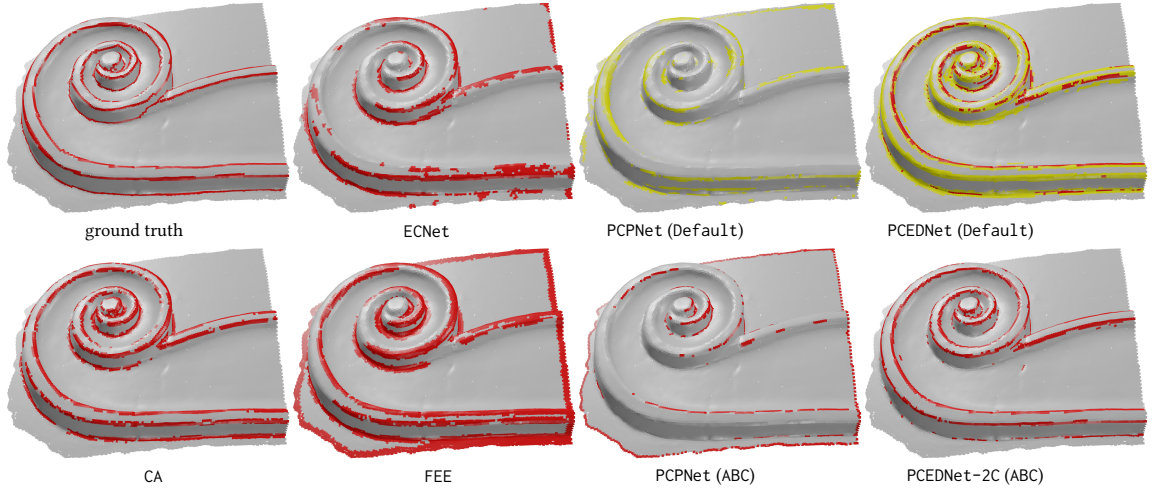


Fig. 14. Model 7 of the SHREC dataset. Results for CNN and FC can be found in the joined website.

by the lower scores obtain by all approaches, in comparison to the other datasets. In particular, PCPNet (Default) fails at classifying edge points (MCC = 0). PCPNet (ABC) produces better results, but relatively low scores as it detects borders as edges, which increases False-Positive detection. On this dataset, ECNet tends to produce noisy and thick edges, getting lower score than CA. CA and FEE (we use $r=2$, $R=4$ and $\text{th}=0.16$ for this dataset) produce more convincing results, with CA reaching MCC= 0.39. CNN (Default) get the best scores on this dataset (both MCC and F1), but the same architecture trained on SHREC gets lower detection rate. Both FC and PCEDNet show better stability w.r.t. the training set (MCC ≈ 0.4 for all variants), but lower score than CNN. Regardless to the quantitative analysis, the results produced by PCEDNet (Default) are very interesting on this dataset. By enforcing the detection of both smooth and sharp edges, it better adapts to the smooth nature of the analysed objects and it provides very pertinent results as illustrated in Figure 14.

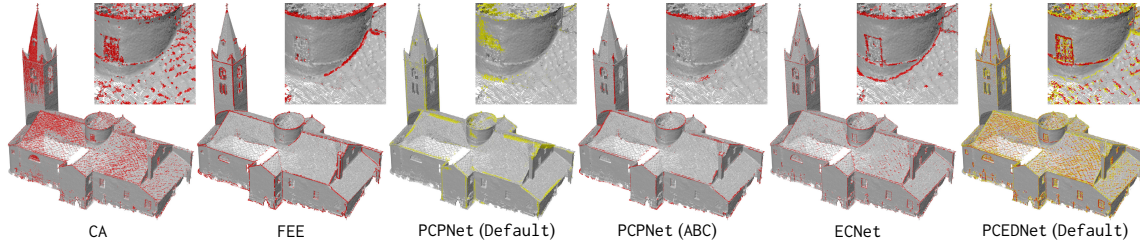


Fig. 15. [Lans](#) model. Results for CNN and FC can be found in the joined website.

5.4 Visual evaluation

In this section we present visual results on acquired datasets without ground truth labelling. All these scenes are presented in more details in the accompanying video and in the joined website. For all the results presented in this section, we compare PCPNet (Default), PCPNet (ABC) and ECNet (on smallest scenes only), FC (Default), CNN (Default), PCEDNet (Default), CA and FEE. Table 9 shows precomputation (GLS) and classification times for all approaches. We see that processing time for PCEDNet (including precomputation) remains of the same order of magnitude than less robust approaches as CA and FEE, and outperforms PCPNet and ECNet (up to two orders of magnitude). Once trained, our approach also avoids the tedious parameter tuning of geometric methods.

Figure 15 represents a part of [Lans](#) without outliers and with very few noise. In this example, FEE detects larger scale edges cleanly, yet it misses fine details. CA detects edges, but it still struggles with surface noise and irregularities. PCPNet has an improved behavior over the noisy model and is able to detect smooth-edges. However, it still fails at classifying sharp-edges. Similarly to FEE and PCPNet, FC extracts large scale edges leaving out finer details, which highlights the importance of scale separation layers in PCEDNet network architecture. Both CNN and PCEDNet produce visually convincing results, but CNN does not detect some fine details that are adequately detected by PCEDNet. ECNet also produces good results on this example, detecting most of the edges and some of the thin details.

Figure 16 presents the behavior of each method when processing models with important noise and lots of outliers. As observed on synthetic datasets, ECNet is strongly penalized by the outliers, and most of the flat areas are misclassified as edges. CA detects all the edge points on the synthetic model but it also considers the outliers as edges. PCPNet classification is weakened by the outliers and does not provide any positive results. FC shows results similar to CA, the network is capable of extracting different edges, yet it is still very sensitive to outliers. CNN and PCEDNet both obtain a high recall on edges, with PCEDNet being the least sensitive to noise.

CNN, FC and PCEDNet rely on the same parameterization. We thus provide in Figures 17 a closer comparison of the results produced by these architectures. In Figures 17, even though all networks generate similar results, the CNN and FC become less accurate when processing irregular surfaces as trees, cars, light poles, etc.

Figure 18 shows how our approach performs on a large point cloud (6M points) in comparison with CA and FEE (other approaches require too much memory/time). [Munich](#) exhibits common irregularities of acquired data, i.e. variable point densities, large gaps, scan noise, and volumetric objects (e.g., trees). PCEDNet (Default) produces cleaner detection and is less affected by acquisition artefacts than the other approaches.

5.5 Interactive learning

As shown in Table 5, PCEDNet requires very low training time, and is stable for very small training sets as our Default. We illustrate how such a flexible network can be trained interactively to better adapt to user wishes and data specificity.

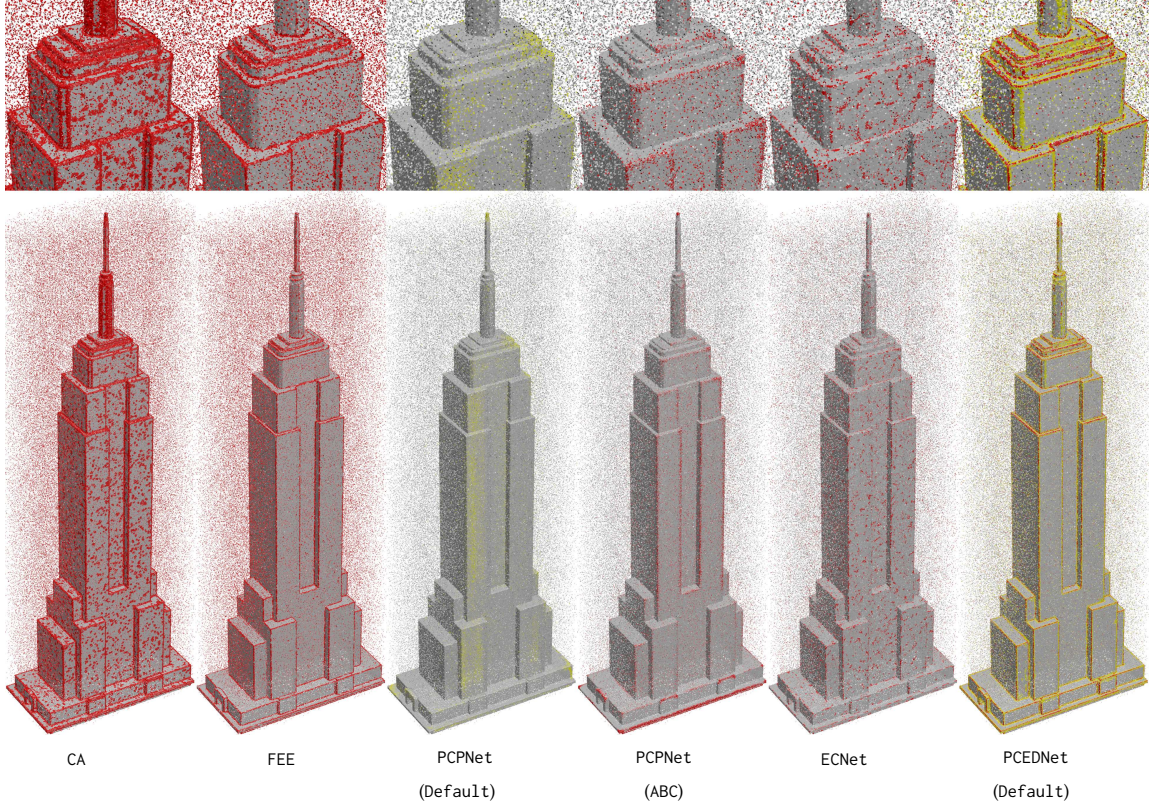


Fig. 16. **Empire** model. This point cloud contains a clean structure with a severe amount of outliers. Results for CNN and FC can be found in the joined website.

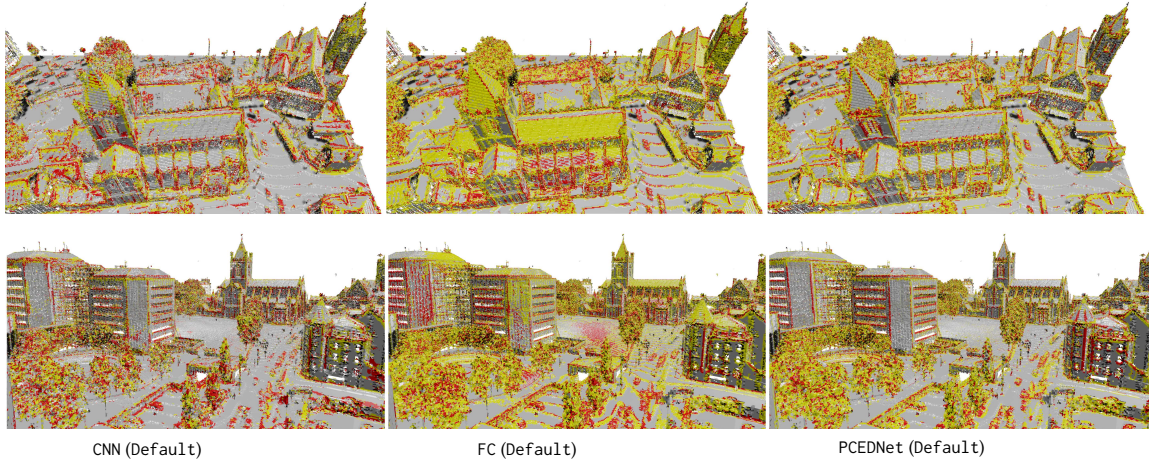


Fig. 17. **Church**. Results for FEE, FC and PCPNet can be found in the joined website.

Our interactive training system performs as follows: the user loads a point cloud on which GLS descriptors are precomputed. This is done in less than 20 seconds for 1M points. Then, the user manually labels some points of the two

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Fig. 18. [Munich](#) model (see Results for CNN and FC in the joined website).

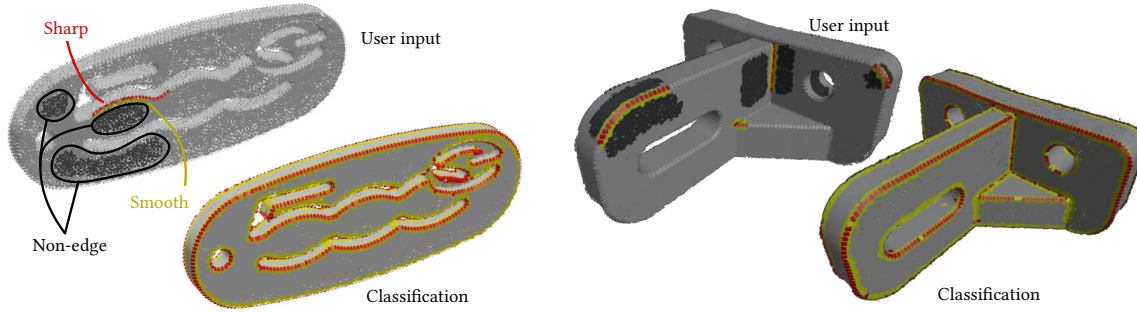


Fig. 19. Interactive training: user inputs and classification results.

classes (sharp edge and non-edge) or the three classes (sharp edge, smooth edge and non-edge). We observed that the non-edge class should contain more points than the two others. This training sets are provided to the PCEDNet network initialized with random values, which learns for 5k epochs in around 10 seconds for approximately 10k input points. As for any other dataset, the number of points per class is automatically balanced during training. Once trained, the network classifies the whole point cloud in around 2 seconds per 1M points. Upon classification, the user can refine the training set according to the network output. If he does so, the network is trained again with the updated learning sets (as training is fast enough and modifying the previous training is less efficient).

We illustrate in Figures 1-c and 19, and in the accompanying video how this tool can be used to achieve high quality classification while allowing the network to infer different edge definitions depending on the user input.

5.6 Complementary experiments

Variation of sampling (minimum scale). The features computed in the SSM are influenced by the minimum scale $s_{\min}$, estimated from the density of the point cloud. We show in Figure 20 how our approach behaves when changing the point cloud density by subsampling, while keeping the automatic estimation of $s_{\min}$. This is illustrated on the Loudun tower, initially composed of 35 millions points, and subsampled down to 15, 5 and 1 million points. Unsurprisingly, decreasing the resolution reduces the quantity of details and leads to thicker edges. However, our classification remains stable and PCEDNet still finds the position of edges, even for low densities, and without requiring the user to set any parameter value.

Variation of maximum scale. We also show in Figure 21 how our classification behaves when changing the maximum scale. Thanks to the logarithmic scale sampling and the scale invariance property of the SSM entries, our approach provides stable results even though the maximum scale is divided by 10 or multiplied by 2.5.

Surface reconstruction algorithm. Our network is parameterized using the Algebraic Point Set Surfaces (APSS) [Guennebaud and Gross 2007], which are known to be stable and reliable even at large scales. We illustrate in Figure 22 the performance of our classifier when computing the parameterization with different approaches: covariance plane fitting (also used in Bazazian et al. [2015]), plane-based point set surfaces [Alexa et al. 2001] and algebraic sphere fitting (same fitting as APSS but without the Moving Least Squares -MLS- projection). For each variant we compute similar values as our GLS descriptor, with derivatives estimated using finite differences. We clearly observe that the use of sphere fitting rather than plane fitting improves the classification, and the best results are always obtained using MLS projection.

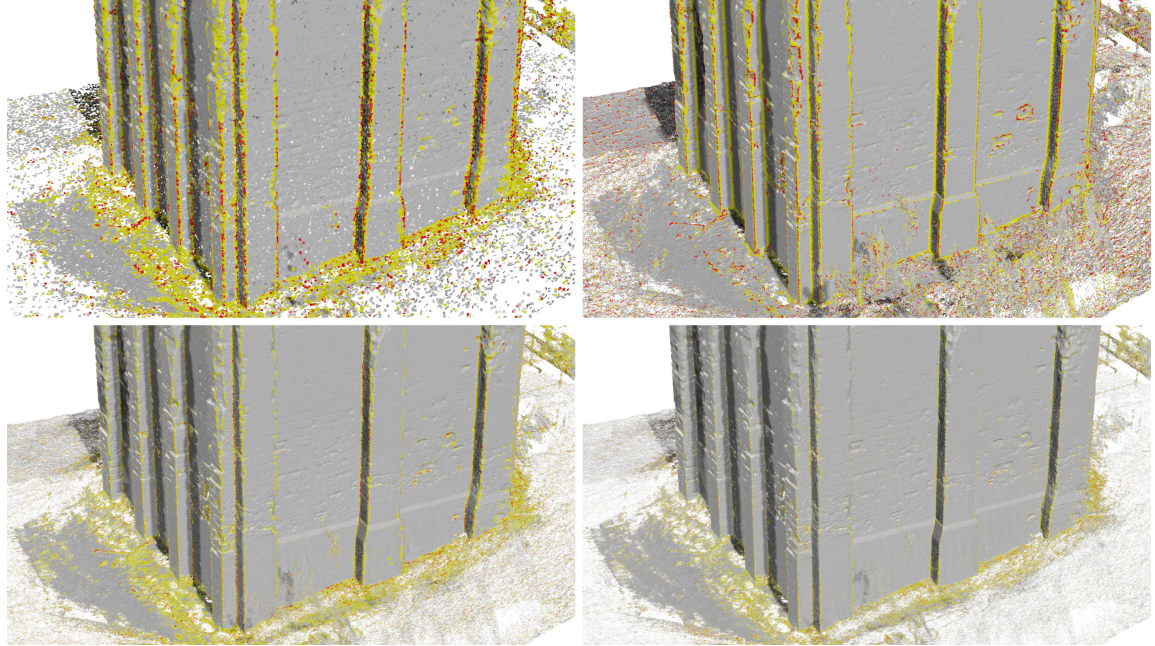


Fig. 20. [Loudun](#): PCEDNet classification with different densities: 1, 5, 15 and 35 millions points from top left to bottom right.

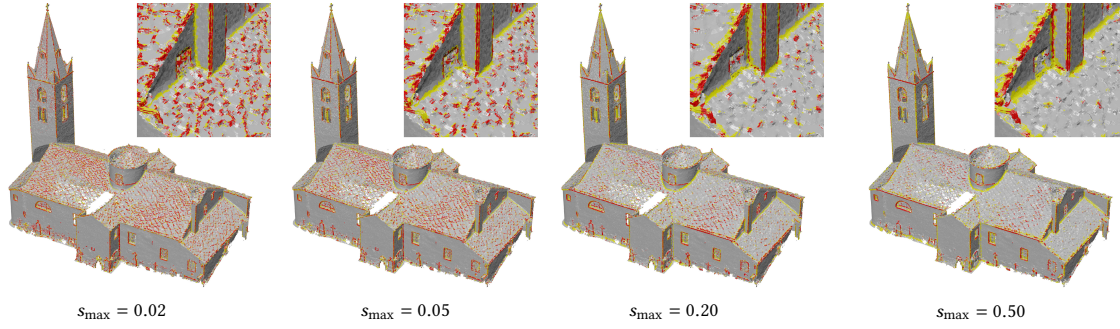


Fig. 21. Classification results when varying the maximum scale when computing the GLS for the analyzed object.

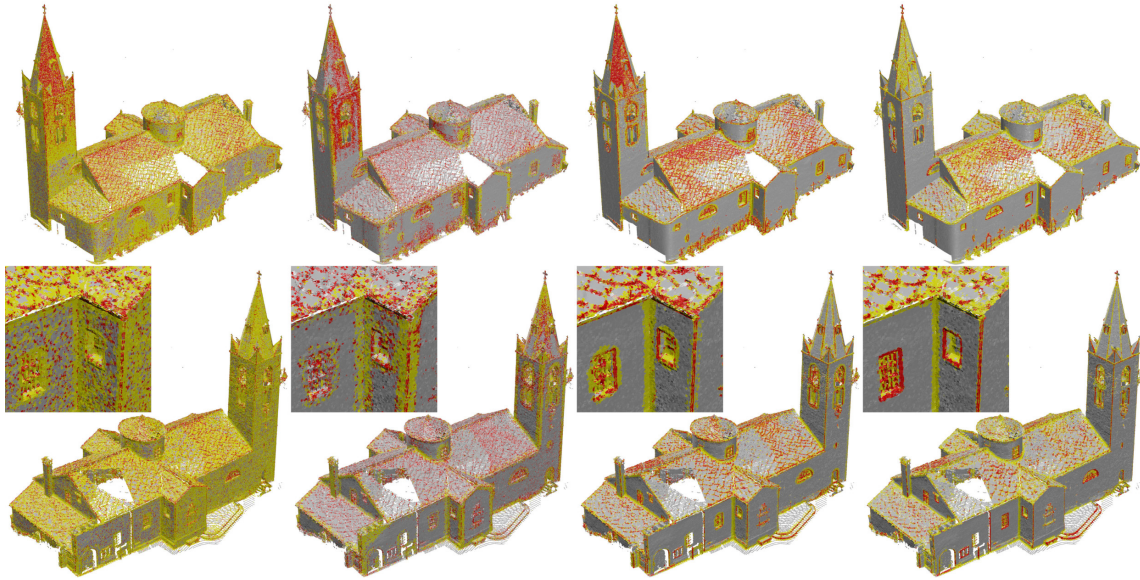


Fig. 22. Impact of the surface reconstruction algorithm on the classification. From left to right: covariance plane fitting (used by Bazazian et al. [2015]), point set surfaces [Alexa et al. 2001], algebraic sphere fitting, algebraic point set surfaces [Guennebaud and Gross 2007] (used in this work).

6 DISCUSSION AND CONCLUSION

We introduced a new parameterization together with its dedicated neural network architecture (PCEDNet) specially designed for the classification of edges in point clouds. PCEDNet outperforms both state of the art methods such as CA, FEE, ECNet and PCPNet, and baselines as CNN and FC. PCEDNet is also remarkably compact by being only composed of about 2100 weights. Given this small size, it is faster than the other approaches tested in this work. Both CNN and PCEDNet achieve similar very good results on synthetic point clouds, which shows that our parameterization based on GLS descriptors is very efficient to encode the point clouds features required for edge classification. Coupled with PCEDNet, it provides a very compact multi-scale representation that captures local geometric properties with reduced sensitivity with respect to noise, as can be seen on the various tests performed on real point cloud scans. The training

and classification of our approach is also sufficiently fast to enable interactive training and classification from direct user inputs.

Limitations: APSS requires oriented normals, which may be tedious to compute accurately in some cases. For all our experiments with point clouds without normals, we got good classification results by estimating consistent normal vectors using Meshlab [Cignoni et al. 2008], without requiring human intervention. An interesting future work would be to consider alternative fitting techniques that do not require oriented normals [Chen et al. 2013b]. Regarding performance, SSM precomputation is currently the bottleneck of the approach, however we believe that a GPU implementation would enable near real-time classification, the most computationally intensive task being the neighborhood queries. Theoretically, SSM is by nature limited to surfaces only, alternative representations [Digne et al. 2018] might be considered in future work to handle lines and volumes.

Perspectives: Other experiments may be conducted to improve the network layout, for instance n by n scales concatenation. An interesting direction for future work could be the study of the extension of this architecture to other geometrical labelling tasks, but also to semantic analysis.

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APPENDICES

A GLS DESCRIPTORS AND DERIVATIVES

The APSS [Guennebaud and Gross 2007] defines a scalar field $S(\mathbf{p})_{\mathbf{u}} = [1 \ \mathbf{p}^T \ \mathbf{p}^T \mathbf{p}] \cdot \mathbf{u}$, where $\mathbf{u} = [u_c \ u_t \ u_q]$ is the vector of field parameters. The parameters of the algebraic sphere are obtained by normalizing these field parameters: $\hat{\mathbf{u}} = \mathbf{u} / \sqrt{\|\mathbf{u}_t\|^2 - 4u_c u_q}$. In the GLS [Mellado et al. 2012], the algebraic sphere parameters are reparameterized to

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compute its geometric parameters: $\tau = S(\mathbf{p})_{\hat{\mathbf{u}}}(\mathbf{p})$ the local relief, $\eta = \frac{\nabla S(\mathbf{p})_{\hat{\mathbf{u}}}(\mathbf{p})}{\|\nabla S(\mathbf{p})_{\hat{\mathbf{u}}}(\mathbf{p})\|}$ the normal vector and $\kappa = 2\hat{u}_q$ the mean curvature.

The Scale-Space Jacobian of the GLS parameters is defined as a 5×4 matrix:

$$\begin{bmatrix} \frac{\delta \tau}{\delta \mathbf{x}} & \frac{\delta \eta_x}{\delta \mathbf{x}} & \frac{\delta \eta_y}{\delta \mathbf{x}} & \frac{\delta \eta_z}{\delta \mathbf{x}} & \frac{\delta \kappa}{\delta \mathbf{x}} \\ \frac{\delta \tau}{\delta t} & \frac{\delta \eta_x}{\delta t} & \frac{\delta \eta_y}{\delta t} & \frac{\delta \eta_z}{\delta t} & \frac{\delta \kappa}{\delta t} \end{bmatrix},$$

where $\delta \mathbf{x}$ and δt are the derivatives in scale and space respectively. k_1 is computed by projecting $\frac{\delta \eta}{\delta \mathbf{x}}$ on the surface tangent plane, which provides an estimate of the second fundamental form.

B SCORES USED FOR QUANTITATIVE COMPARISON

The scores used in Section 5 are defined as follows:

Precision (also denoted positive predictive value – PPV) measures the proportion of positive identifications that are actually correct (the higher, the better). It is defined as:

$$\text{precision} = \frac{TP}{TP + FP}.$$

Recall (also denoted sensitivity, hit rate, or true positive rate – TPR) measures the proportion of actual positives that are correctly identified (the higher, the better). It is defined as:

$$\text{recall} = \frac{TP}{TP + FN}.$$

The Matthews Correlation Coefficient (MCC) is a correlation coefficient between the observed and predicted binary classifications; it returns a value in $[-1 : 1]$. A coefficient of 1 represents a perfect prediction, 0 no better than random prediction and -1 indicates a total disagreement between prediction and observation. It is defined as:

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}.$$

F1 score is a measure of a test accuracy. For binary classification, F1 is defined as follows:

$$\text{F1} = 2 \cdot \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}.$$

Accuracy measures is the fraction of predictions our model got right. For binary classification, accuracy is defined as:

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}.$$