Title:
Invariance Class-based Surface Reconstruction using Deep Learning

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Introduction:

Geometrical operations are defined in ISO standards on geometrical product specifications and verification (GPS) [1] for obtaining ideal and non-ideal features to represent functional surfaces on mechanical parts. These geometric features should be categorized by their geometrical properties for further geometry processing. In the context of ISO GPS, surface portions are determined by their kinematic invariance and are classified into planar, cylindrical, helical, spherical, revolute, prismatic and complex surfaces.

In this paper, geometric features based on the discrete representation enabled by the Skin Model Shapes paradigm are investigated. The discrete representation of surfaces is based on point cloud obtained by tessellation on either nominal model or Skin Model Shapes[2] or by measuring manufactured parts. Many research activities have contributed to invariance class identification and surface reconstruction of mechanical parts. Gelfand et al. proposed a partitioning method based on slippage analysis that is able to identify surface patches with points' normal information [3]. A probabilistic description by pre-defined semi-parametric models [4] permitted to enrich the work of invariant surface identification. Schnabel proposed Random Sample Consensus (RANSAC) based method to detect surface primitives in unorganized point clouds [5]. The work can be used for single surface reconstruction with a pre-defined primitive set. Cai et al. proposed a three-step hybrid process towards ISO GPS for partitioning mesh and point cloud into surface portions and identifying each of them as one of the seven invariance classes of surfaces [6]. The aforementioned mentioned methods are able to address the invariant surface identification and reconstruction by either pre-defined parameters or manually-established models. However, the performances of these methods are limited due to the need of prior knowledge and the high computational complexity.

As a well-known deep learning algorithm in computer vision to tackle problems such as image classification, face recognition, etc., Convolutional Neural Network (CNN) has been widely investigated and applied in Computer-aided Design (CAD) due to its effectiveness in capturing the input data features. Nevertheless, the implementation of CNN on point cloud for CAD is hindered due to the sparsity, randomness and non-structure of point clouds. Existing deep learning strategies for point cloud identification and classification [7] can be categorized into multi-view based methods, Volumetric based methods and point based methods. Compared to 2D and image data, 3D data such as point clouds has many advantages for representing mechanical parts given an extra data dimension. Meanwhile, the large number of labeled data required for training a CNN can be achieved with relatively little effort by geometry processing on point clouds rather than proposing a novel theory for 2D and image data such as Generative adversarial networks (GANs) [8].

In this regard, an automatic algorithm for surface reconstruction by its invariance class is proposed in this paper based on deep learning architecture to speed up the geometry processing. Regarding the specificity of the point cloud derived from simulations and measurements, a multi-view-based strategy is implemented by dimension reduction using point cloud projection. The extracted view-wise features are aggregated into a discriminative global representation for training neural networks. The method overview, point cloud pre-processing, training process and the reconstructed results are presented in the following sections.

Method Overview:

An overview of the proposed surface reconstruction method on point cloud is shown in Fig. 1. Point clouds obtained from simulations or measurements can be decomposed into surface portions by partitioning operations using the approach described in [9]. In order to overcome the sparsity, randomness and non-structure of the point clouds scattered in 3D space, a pre-processing step of dimension reduction is conducted by the projection within the principle directions. A deep neural network is trained with labeled point cloud and is used in the following step to identify the invariance class of the input data. Finally, the geometric descriptors of each point cloud can be obtained for surface reconstruction since the ideal geometrical features are guaranteed by a fitting step.

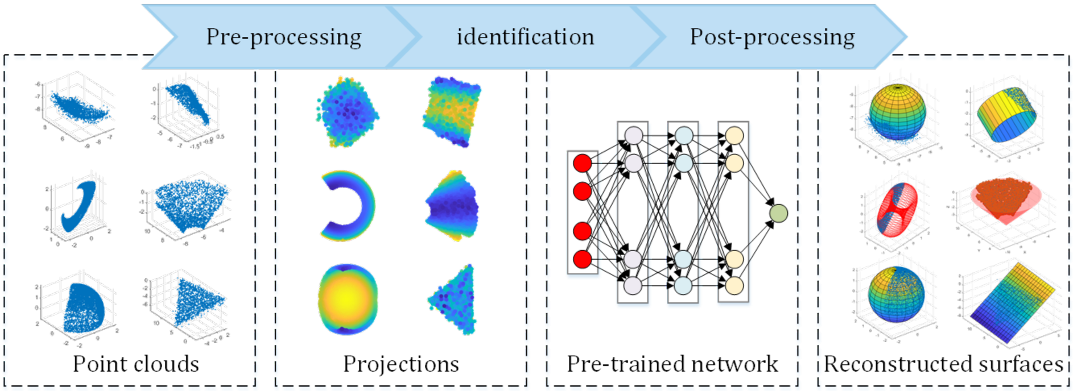

Fig. 1: Overview of the proposed surface reconstruction method based on invariance class identification

Generation of 2D Projections from Point Clouds:

Geometrical surfaces are derived from either the CAD models in the simulation process or the measurements in the reverse engineering process. The reconstructed information of such surfaces includes both the actual shape and dimensions as well as geometric deviations of the surface. In early engineering design stages, point clouds are obtained from CAD models by tessellation where deviations might be incorporated considering the simulation purposes. During later design stages, manufacturing process simulations and even the prototypes of mechanical parts are available. Point clouds can thus be obtained from the "observation" [2] in these stages with geometric uncertainties.

In this context, the representation of point clouds for geometry processing should be feasible and robust with limited computational cost for both nominal surfaces and non-ideal surfaces affected by noise or other imperfections, such as non-uniform sampling, low sampling density, misalignment and missing data, etc. Therefore, as a statistical method to compute the most meaningful basis to re-express the point sets, Principal Components Analysis (PCA) is implemented in our method for extracting the principal axes of point clouds with different invariance classes.

Considering a discrete point cloud partitioned from a workpiece, the covariance matrix is defined as:

$$M_{cov} = \sum_{i=1}^{n} (x_i - O_{pca})(x_i - O_{pca})^T \tag{2.1}$$

where O_{pca} is the origin determined as the centroid of the points of the point cloud. The first principal axis is the eigenvector corresponding to the largest eigenvalue. The two other principal axes are obtained from the remaining eigenvectors.

Based on the analysis, the projection process starts with the normalization of point clouds into a unit sphere, which addresses the problem of sparsity and randomness of the 3D data. Then the normalized point cloud is mapped along the first principal axis. A filtering process is conducted in the mapping process to overcome the sparsity by eliminating details of the mapping patterns. In the end, the mapping patterns are transferred into images to address the 'non-structure' problem of the point clouds. However, the mapping along the first principal axis is not enough for surface invariance class identification due to the missing information of the altitude of each point along the first principal axis. In this regard, the altitude along the first principal axis is transferred into specified colors during the mapping process to maintain the information. Examples can be found in Fig. 2 with the point cloud mapping results of different types of invariance classes.

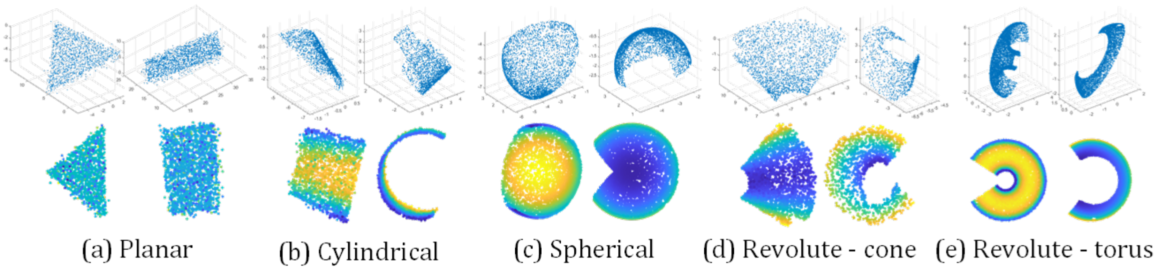

Fig. 2: The projection of 3D point clouds to 2D image, classified by their invariance classes. The first row is the original point cloud and the second row is the mapped image of each point cloud.

It can be seen from the figure that some of the information such as the edges of the surface and the noises are filtered out during projection process, which is the major cost in the training process of point-based deep learning methods such as PointNet[10].

Transfer learning for surface identification:

The objective of transfer learning is to transfer the knowledge from the existing task to a new target task. It is widely applied regarding the limited labeled examples or the significant amount of training time in the new tasks. However, transfer learning is implemented in this paper since the pre-trained CNNs contain generic and reusable features in the first few layers that are directly related to our problem.

As a large network structure with 60 million parameters and 650,000 neurons, the pre-trained AlexNet on the ImageNet data set is employed in this paper for transfer learning. The last three layers of the AlexNet are fine-tuned for the invariant surface identification and the fully connected layer is set to have the same size as the invariance classes defined in the training set.

In order to verify the performance of our method, the experiments is conducted by transfer learning on an open-source benchmark dataset from SHREC'22(http://shrec.ge.imati.cnr.it/shrec22_fitting/). It is a large-scale dataset with 3D segments represented as point clouds. Surface primitives include planes, cylinders, spheres, cones and torus that are classified by their invariance classes. 46,000 point clouds are contained in the dataset as the training set and 925 point clouds are used as the test set. The point clouds could be clean or perturbed by noises following a variety of distributions.

The training is performed on a workstation equipped with a 1.70 GHz Intel(R) Xeon(R) CPU, 16 GB RAM, and the Windows 10 operating system. Our approach took 5h to train the AlexNet for the SHREC'22 dataset (6 epochs). The validation accuracy reached 87.61% after training.

Surface Reconstruction based on Invariance Class:

In the context of ISO GPS, the association is defined to fit the pre-defined features to non-ideal point clouds considering specified criteria including Gaussian (least squares), Chebyshev and maximum inscribed or minimum circumscribed fittings. Details about surface reconstruction towards ISO GPS can be found in [11]. When the invariance class of a point cloud is identified by the fine-tuned AlexNet, an ideal feature defined by a parametrized equation can be guaranteed to obtain a reconstructed surface for reverse engineering.

Experiments:

Different approaches from the literature review are compared in the experiments regarding a variety of variations point cloud specificity as summarized in Table 1. Our method is able to deal with different types of point cloud specificity while other methods are limited by their performance. We show that our method, while simple and effective, is robust to various kinds of input corruptions. It should be highlighted that the computational time of our method for each point cloud is less than 0.5 seconds on average while the other methods take several minutes to obtain the surface type information.

Table 1: Performance of different approaches regarding point cloud specificity

No.	**Deviation** [1]	**Sampling**[2]	**Ref [3]**	**Ref [4]**	**Ref [5]**	**Ref [6]**	**Ours**
1	C	Uni	•	•	•	•	•
2	C	Und		•	•	•	•
3	C	M	•	•	•		•
4	S	Uni	•	•	•	•	•
5	S	Und		•	•		•
6	S	M	•	•	•		•
7	U	Uni	•	•		•	•
8	U	Und					•
9	U	M	•	•			•
10	G	Uni	•	•	•	•	•
11	G	Und			•		•
12	G	M	•	•	•		•
Remark	-	-	*	**	***	****	

[1] C: Clean; S: Systematic deviations; U: Uniform random deviations; G: Gaussian random deviations;
[2] Uni: Uniform; Und: Under-sampling; M: Missing;
* Normal information needed; Parameter needs to be tuned for different noise deviations.
** Pre-defined statistical models; High computation complexity.
*** Pre-defined models; Parameter needs to be tuned for different noise deviations.
**** Normal information needed; Parameter needs to be tuned for different noise deviations.

Conclusions:

In this paper, a method based on deep learning is proposed for surface invariance class identification. Point clouds tessellated from CAD models or obtained from measurements are used as input without local parameters such as normal information or k-nearest neighbors as in other approaches. The method is tested on an open dataset and it enables robust surface reconstruction for reverse engineering with little computational cost in the context of ISO GPS. Future work will focus on the establishment of key indicators for estimating the reconstruction performance to benefit product development phases.

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