PCPNet: Learning Local Shape Properties from Raw Point Clouds

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Traditional Approaches

Estimating differential quantities using polynomial fitting of osculating jets, Cazals and Pouget, 2005

Algebraic Point Set Surfaces, Guennebaud and Gross, 2007

Surface reconstruction from unorganized points, Hoppe et al., 1992

Examples:

PCA

Jet fitting

MLS Sphere Fitting

Estimating differential quantities using polynomial fitting of osculating jets, Cazals and Pouget, 2005
Traditional Approaches

• Sensitive to parameters like patch size
• Acceptable parameter settings depend on data conditions like noise strength, feature size, …
Deep Learning Approaches

- Robust to a large range of conditions
- Problem: invariance to the point order

mapping to feature vector:

\[ F(p_1, p_2, p_3, \ldots) \neq F(p_3, p_1, p_2, \ldots) \]
Deep Learning Approaches: PointNet

- **PointNet**: Deep Learning on Point Sets for 3D **Classification and Segmentation**, Qi et al., CVPR 2017

![Diagram showing PointNet's architecture and feature extraction process.](image)
Deep Learning Approaches: PointNet

- Using only fully global features or fully local features limits accuracy
- Not well suited for normal estimation
• Instead, using features of a **local patch** gives better accuracy
• State-of-the-art for normal and curvature estimation

*PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space*, Qi et al., NIPS 2017
PCPNet Architecture

Pre-processing (center and scale)

Point Functions

Symmetric Operation

Regressor

deep network, trained end-to-end

\[
 n(p_i, P) = \sum_{p_j \in P_i} h(p_j) = H(P_i) \rightarrow \kappa_1(p_i, P), \kappa_2(p_i, P)
\]

point cloud \( P \)

and point \( p_i \)

local patch \( P_i \)

feature vector of \( P_i \)

local properties at \( p_i \)
Point Features

\[ p_i \]
\[ p_{j_1} \quad h(p_{j_1}) \]
\[ p_{j_2} \quad h(p_{j_2}) \quad \sum_{p_j \in P_i} h(p_j) = H(P_i) \]
\[ p_{j_3} \quad h(p_{j_3}) \]
\[ \vdots \]

1024D feature vector for each point in the patch:

\[ p_{j_1} \xrightarrow{\text{QSTN}} \]
\[ p_{j_2} \xrightarrow{\text{rotation}} \]
\[ p_j \xrightarrow{\text{FNN}_1} \]
\[ g(p_{j_1}) \xrightarrow{\text{STN}} \]
\[ g(p_{j_2}) \xrightarrow{\text{linear transform}} \]
\[ g(p_j) \xrightarrow{\text{FNN}_2} \]
\[ h(p_j) \xrightarrow{\text{1024D}} \]

\[ n(p_i, P) \]
\[ \kappa_1(p_i, P) \]
\[ \kappa_2(p_i, P) \]
Point Functions: Two Views

\[ h(p) = [h_1(p), h_2(p), \ldots, h_{1024}(p)] \quad \text{with} \quad h_l : \mathbb{R}^3 \rightarrow \mathbb{R} \quad \quad H_l(\mathbb{P}_i) = \sum_{p_j \in \mathbb{P}_i} h_l(p_j) \]

- Point functions \( h_l(p) \) can be seen as \textbf{space probes}
- Sum over all points \( H_l(\mathbb{P}_i) \) is a \textbf{density estimate}

- Point functions \( h_l(p) \) can be seen as \textbf{convolution kernels}
- Sum over all points \( H_l(\mathbb{P}_i) \) is a \textbf{convolution}

\( \bullet \) positive \quad \bullet \) negative \quad \( \bigcirc \) close to 0 \quad (values have been 0-centered)
• Three radii, 3072 point functions, concatenate patch features

\[
\sum_{p_j \in \mathbb{P}^1_i} h(p_j) = H(\mathbb{P}^1_i)
\]

\[
\sum_{p_j \in \mathbb{P}^2_i} h(p_j) = H(\mathbb{P}^2_i)
\]

\[
\sum_{p_j \in \mathbb{P}^3_i} h(p_j) = H(\mathbb{P}^3_i)
\]

\[
\begin{bmatrix}
H(\mathbb{P}^1_i) \\
H(\mathbb{P}^2_i) \\
H(\mathbb{P}^3_i)
\end{bmatrix} \rightarrow
\begin{bmatrix}
n(p_i, \mathbb{P}) \\
\kappa_1(p_i, \mathbb{P}) \\
\kappa_2(p_i, \mathbb{P})
\end{bmatrix}
\]
Results
Full shape dataset
each shape sampled with 100k points
each point can be a patch center

Sampling variations
noise std. deviation
(in percentage of bounding box diagonal)
Unoriented Normal Estimation

average over dataset

relative angle error

angle error (deg.)

noise strength

0

0.1

Jet small

Jet medium

Jet large

ours

Jet small

Jet medium

Jet large

ours

Boulch et al. 2016

PointNet

Jet large

ours

Maximum Curvature Magnitude Estimation

max. curvature error

ours  Jet small  Jet medium  Jet large

norm. curv. error

0  3
Oriented Normal Estimation & Surface Reconstr.

point cloud

jet small + MST orient. prop.

ours

angle error (deg.)

0

90
Limitations

• Usually generalizes well, but may fail on patch configurations that are very different from those given in the training set

• Ambiguous orientations for flat surfaces larger than patch radius

• Slower to evaluate than PointNet, speed is ~ 200 points / second on a single Titan XP
Conclusions

• Point Functions can be seen as learned continuous 3D kernels
• Convolving these kernels with a point cloud gives rich features that can be used for state-of-the-art normal and curvature estimation

Website:
geometry.cs.ucl.ac.uk/projects/2018/pcpnet

Code:
github.com/paulguerrero/pcpnet
Thanks!

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Acknowledgements:
This work was supported by the ERC Starting Grants Smart-Geometry (StG-2013-335373) and EXPROTEA (StG-2017-758800), the Open3D Project (EPSRC Grant EP/M013685/1), the Chateaubriand Fellowship, chaire Jean Marjoulet from Ecole Polytechnique, FUI project TANDEM 2, and a Google Focused Research Award.