Abstract—Effective feature representation from Airborne Laser Scanning (ALS) point clouds used for urban modeling was challenging until the advent of deep learning and improved ALS techniques. Most deep learning techniques for 3-D point clouds utilize convolutions that assume a uniform input distribution and cannot learn long-range dependencies, leading to some limitations. Recent works have already shown that adding attention on top of these methods improves performance. This raises a question: can attention layers completely replace convolutions? We propose a fully attentional model-PointTransformer for deriving a rich point cloud representation. The model’s shape classification and retrieval performance are evaluated on a large-scale urban dataset - RoofN3D and a standard benchmark dataset ModelNet40. Also, the model is tested on various simulated point corruptions to analyze its effectiveness on real datasets. The proposed method outperforms other state-of-the-art models in the RoofN3D dataset, gives competitive results in the ModelNet40 benchmark, and showcases high robustness to multiple point corruptions. Furthermore, the model is both memory and space-efficient without compromising on performance.

Index Terms—Airborne Laser Scanning (ALS), Shape Retrieval, Shape Classification, Self-Attention, Mean Average Precision (MAP), PointTransformer

I. INTRODUCTION

The shape classification and retrieval of roof point clouds in urban modeling is very significant, as the roof is the most informative part of the building. With the development of the Airborne Laser Scanning (ALS) technique, it is easier to obtain the three dimensional (3-D) large scale urban scene rapidly. However, the captured point clouds are sparse, noisy, and incomplete, and there is a vital requirement for robust methods to these issues.

Recent improvements in deep learning techniques and the emergence of 3-D shape datasets such as ModelNet [1], ShapeNet [2] has led to advancements in 3-D shape classification and retrieval. However, deep learning is still not widely explored in remote sensing and Geographic Information System (GIS). Deep learning approaches related to 3-D shape representation can be roughly categorized into view-based, voxel-based and point-based methods. In view-based approaches [3], multiple views of the point cloud are generated and fed to a dense convolutional neural network (CNN) to derive suitable feature representations. The performance of the model is limited by the number of views and leads to high storage, computational requirements. Voxel-based techniques use 3-D CNNs to convert points to voxels, which leads to loss of intrinsic geometric properties of the point cloud. On the other hand, point-based techniques directly utilize raw point clouds to avoid loss of information and are increasingly becoming popular these days. Point clouds are non-uniform, unstructured, unordered, and hence it is infeasible to directly apply convolutions while maintaining order invariance. A pioneering point-based method, PointNet [4] addresses this problem by utilizing symmetric operations to derive a feature representation for point clouds. An improved work PointNet++ [5] utilizes hierarchical grouping of points to capture local and global information. Another work PointCNN [6] learns a χ transformation of the input points for feature learning. All these methods use convolutions and assume a uniform input distribution, which is not valid in real datasets containing various imperfections. Also, convolutions cannot learn long-range dependencies, hence limiting the quality of contextual information derived from the point cloud. Recent works have shown that attention layers on top of these methods improve performance. Attentional ShapeContextNet [7] utilizes sequential attention blocks to derive point features that are max pooled to create a global feature representation but leads to loss in information. Set Transformer [8] uses a similar idea and introduces an attention-based pooling operation but leads to over-fitting due to excess parameterization. On the other hand, Local-to-Global autoencoder (L2G-AE) [9] employs a novel hierarchical attention operation at different levels to derive an information-rich feature representation.

However, this paper explores the possibility of completely replacing convolutional layers with attention blocks. This study’s motivation is that convolutional kernels get activated at specific regions, and similarly, attention layers focus on specific regions of the point cloud. The proposed method - PointTransformer outperforms other state-of-the-art models in a real dataset RoofN3D, and to ensure a fair comparison with previous works; we evaluate the model on standard benchmark dataset ModelNet40. To determine the method’s effectiveness on real datasets, the model is tested on point corruptions like uniform point removal and noise addition. We also partially remove regions in the point cloud to simulate incomplete scans, and the model significantly outperforms other methods in all these cases. The key contributions of our work are as follows:

• Novel approach utilizing transformers to show self-attention can completely replace convolutions in point cloud processing.
• Embedding module to derive an enhanced representation of the point cloud with absolute and relative information.
• Iterative transformers with weight-sharing to successively improve point features without over parameterization.
• Unique grouping mechanism with a routing loss to group semantically similar points and derive region/group-wise

PointTransformer for Shape Classification and Retrieval of 3D and ALS Roof PointClouds

Dimple A Shajahan, Mukund Varma T and Ramanathan Muthuganapathy

Submitted on June, 16 2020
II. RELATED WORKS

The methods for modeling building rooftops from ALS data are categorized into model-driven and data-driven techniques. Model-driven approaches fit the roof points to a given set of roof templates and select the best fit. This method is parametric, resilient to noise, and missing data but requires prior information about the roof shape [10]. There are various data-driven methods like plane fitting, filtering and thresholding, segmentation-based, and learning-based, which are non-parametric and do not require prior information [10]. However, it is affected by the average point density, presence of noise, and missing points in the point cloud [10]. Roof-Shape classification and retrieval are major tasks in 3-D building modeling. A few learning-based methods for roof classification include: Zhang et al. [11] introduced a random forest classifier trained using features extracted from the point cloud and a codebook, Castagno et al. [12] uses a multi-modal architecture to utilize information from satellite images and ALS data. A more recent work, Shajahan et al. [13] introduced a multi-view based deep learning approach for classifying roof point clouds. These limited number of works show that deep learning techniques for shape classification and retrieval of ALS roof point clouds are still unexplored.

We propose a novel point-based deep learning approach robust to various point corruptions for shape classification and retrieval of complete and partial roof point clouds. The remainder of this letter is structured as follows: Section III describes the Methodology, followed by the Experiments and Results in section IV and Section V concludes and suggests possible improvements.

III. METHODOLOGY

Our proposed architecture - PointTransformer as shown in Fig. 1a consists of the following modules:

- Embedding Module
- Transformer Block
- Grouping Module and Routing Loss
- Weighted Group Aggregation

A. Embedding Module

The embedding module, as shown in Fig. 1b is introduced to enhance the input point representation before passing to the attention layers. It consists of two branches - one to encode the absolute position and the other to derive the relative position information, each of size Nx64. These representations are concatenated to create the required embedding of size Nx128. To encode the absolute position information, each point is fed into a Multi-Layer Perceptron (MLP), and a gating operation is done using a Gated Linear Unit (GLU) to selectively propagate the required information. In the other branch, for each point, its corresponding k-nearest neighbors are found before passing to another MLP layer, followed by a max-pooling operation to create a suitable vector. This is further passed to another GLU unit to enhance the derived representation. To make the embedding module robust to variable point cloud size, the value of $k$ is reduced based on the number of points.

$$k = k_0 \times \frac{N}{N_0}$$

where $k_0 = 32$, $N_0 = 1024$ are constants and N is the input pointcloud size.

B. Transformer Block

As shown in Fig. 1a the transformer block derives a query vector Q, key vector K, and value vector V from the derived embedding feature vector. Here Q, K, and V are three feature vectors learnt using independent MLP layers. Then, the attention weights are computed by the dot product of Q and K, followed by a softmax operation to normalize it. The attention weights of size NxN describe the relationship between every pair of points in the input point cloud. This is then multiplied with the value vector to derive a feature representation describing each point. The above operation is referred to as scaled dot-product attention [14] denoted as SDP, as shown in Eq. (1)

$$SDP(Q,K,V) = \text{Softmax}(QK^T/\sqrt{N})V$$

Rather than computing the attention once, a multi-head attention mechanism (MHA) [14] computes the scaled dot-product attention multiple times. This helps the transformer jointly attend to information from different derived relationships from each head. The query vector is added to the output from the MHA operation as a residual connection and is passed onto MLP layers with Relu activation to derive a point representation of size Nx$F_1$. Since we are computing complex
relationships between a large number of points, there is a high chance of sparsity in the attention weights. Hence, the transformer block operations are performed recursively with shared weights to improve the feature representation across M passes. The query vector is derived from the learned point features obtained from the previous pass, while the key and value vectors are retained as the same. This, in turn, extracts new information to enrich the final representation without over parameterizing the model.

C. Grouping Module

A point cloud is characterized by multiple groups of points, each determining a specific region. As an alternative to direct pooling of the derived point representation, we create region-wise or group-wise feature vectors describing the point cloud shape. Based on this idea, we introduce a grouping mechanism shown in Fig. 1c to group semantically similar points. To split the points into groups, probability values are predicted for each point, determining the best group for it. The points are then hard-routed based on these probability values, which implies that a point can belong to only one group, and no residue of the same is passed to the others. This is done using a masking operation to select the points belonging to each group. In each group, a specific feature transformation is applied to the points using an MLP layer followed by a max-pooling operation to select the points belonging to each group. This is shown in Fig. 1c to group semantically similar points. To split the points into groups, probability values are predicted for each point, determining the best group for it. The points are then hard-routed based on these probability values, which implies that a point can belong to only one group, and no residue of the same is passed to the others. This is done using a masking operation to select the points belonging to each group. In each group, a specific feature transformation is applied to the points using an MLP layer followed by a max-pooling operation to create a group feature vector of size $F_2$. The grouping operation is applied in every pass as the transformer block extracts new information in each of them. Since there is no explicit method for the model to identify the best group for each point, at times during training, we route the points to the group corresponding to their second-highest probability. This allows the model to explore all available groups before converging to the best group for a point.

D. Routing Loss

The routing loss is introduced to penalize the model based on the distribution of points among groups. This is to ensure all groups receive enough points to capture region-specific information. This is shown in Eq. (2), where $N_g$ is the number of points assigned to the $g$th group and $N$ is the total number of points in the input point cloud.

$$RoutingLoss, R_L = \sum_{g=1}^{G} \left( \frac{N_g}{N} \right)^2$$

(2)

To provide an intuition, let us assume $f_1$ and $f_2$ to be the fraction of points routed to any two groups. If both these fractions of points are routed to a single group, then the value of routing loss will be higher as $(f_1 + f_2)^2 > f_1^2 + f_2^2$ and similarly, this idea can be extended to G groups.

E. Weighted Group Aggregation

The group aggregation operation combines the group feature vectors obtained from all passes to create a point cloud representation. To select relevant information from these groups, a weight matrix is generated by passing it through an MLP layer, which is normalized using a softmax operation. These weights are multiplied with the corresponding features and then added to derive the global feature vector. This operation is equivalent to $\sum(softmax(ax + b) * x)$ where $x$ denotes the input, $a$ and $b$ represent the weights and bias terms of the MLP layer respectively.

This global feature vector describing the point cloud is passed onto two MLP layers with ReLU activation, batch normalization, and dropout to further enhance it before the classification layer. The model is trained to minimize the cross-entropy loss along with the routing loss, as mentioned above.

IV. EXPERIMENTS AND RESULTS

We have conducted comprehensive experiments to validate the effectiveness of PointTransformer. The details of the experiments are given below.

A. Datasets

The performance of the model is evaluated on a large scale dataset of roof point clouds RoofN3D. Being a new approach and to ensure a fair comparison with previous works, we also evaluate the model’s performance on a standard benchmark dataset ModelNet40. RoofN3D [15] dataset contains ALS point clouds of buildings of New York city and has 1,18,073 roof shapes split into three categories - Saddleback, Two-sided Hip, and Pyramid. The dataset is uniformly split into 95,632 train, 10,627 validation, and 11,814 test samples. ModelNet40 [11] contains CAD models from 40 categories split into 9,843 train and 2,468 test samples. We use the pre-processed dataset provided by PointNet++ [5] with the standard train-test split for accurate comparison.

B. Experiment Setting

We use the following hyperparameters to train PointTransformer for the classification task. The model derives 128 size vectors from the embedding module, subsequently fed to the transformer block with hidden size $F_2=512$. We choose $M=4$ and $G=4$ for our experiments. The network is trained using Adam optimizer with a batch size of 24 and an initial learning rate of 0.001, which is reduced by a factor of 0.7 every 30 epochs. We ran our experiments on an NVIDIA GTX 1080Ti GPU.

C. Shape Classification and Retrieval

We train the model on the RoofN3D and ModelNet40 datasets for classification and use the trained models to evaluate the retrieval scores. By default, we select 1000 points uniformly sampled for the RoofN3D dataset and 1024 points using farthest point sampling for ModelNet40. The point clouds are augmented by translation, scaling, point dropout, and the addition of a gaussian jitter. To evaluate the shape retrieval scores, we extract the feature vectors from the penultimate MLP layer for every sample in the test set. We sort the most relevant shapes for each query by cosine distance and compute the Mean Average Precision (MAP) score.
TABLE I: Shape Classification and Retrieval results on RoofN3D

| Method       | Accuracy (%) | MAP (%) |
|--------------|--------------|---------|
| PointNet     | 96.57        | 90.8    |
| PointNet++   | 97.03        | 94.3    |
| PointCNN     | 97.39        | 94.37   |
| SO-Net       | 97.78        | -       |
| MVCNN-SA     | 97.76        | 96.94   |
| PointTransformer | 97.86   | 94.5    |

TABLE II: Shape Classification and Retrieval results on ModelNet40

| Method       | Accuracy (%) | MAP (%) |
|--------------|--------------|---------|
| MVCNN        | 90.1         | 79.5    |
| PointNet     | 89.2         | 70.5    |
| PointNet++   | 90.7         | 83.2    |
| SO-Net [2k]  | 90.9         | -       |
| PointCNN     | 92.2         | 83.8    |
| ASCN         | 90.9         | 71.83   |
| L2G-AE       | 90.64        | -       |
| PointTransformer | 91.07   | 83.5    |

Tables I and II compare our shape classification and retrieval results with other methods on the RoofN3D and ModelNet40 datasets. PointTransformer outperforms all state-of-the-art models in the RoofN3D dataset signifying its effectiveness in real datasets with multiple imperfections. The model performs better than PointNet++ [15], SO-Net [18] and attention-based methods like L2G-AE [9], ASCN [17] in the ModelNet40 dataset. The first two rows in Fig. 2 show samples retrieved for a full shape query from both datasets. In the roof retrieval case, complex substructures present in the query shape are retained in the retrieved samples.

Fig. 2: Shape retrieval using complete (top 2 rows) and partial query (bottom 2 rows)

D. Test for Robustness

The model trained for the classification task is tested on different forms of simulated point corruptions - reduced point density, noise addition, and partial shape removal. To reduce point density, lesser number of points are uniformly sampled from the point cloud at various percentages. For the noise test, random Gaussian noise of a particular standard deviation is added to specific points in the point cloud. To simulate incomplete scans, partial point clouds are created by randomly sampling a point and removing its n-nearest neighbors. Fig. 3 shows some samples from both these datasets with the simulated corruptions. To test for robustness in shape retrieval, we use partial point clouds as the query shape, and the closest matching complete point clouds are retrieved to compute the MAP score. Shape classification and retrieval results for 75% partial shape are shown in Table III. We show the variation in performance with various levels of corruption as a graph in Fig. 4. It is evident from the graph that PointTransformer significantly outperforms other methods in uniform point removal and addition of noise, especially on higher levels of corruption. As per our observation, PointCNN does not perform well in noisy points, which could be the reason for lower performance in the RoofN3D dataset.

E. Visualising the Model

In Fig. 5, we visualize the attention maps and group formation learnt by PointTransformer. As seen from Fig 5a, the model distributes its attention across all points in the initial pass but later attends to specific regions as it tries to iteratively improve the feature representation. Semantically similar points are grouped together, describing a particular shape in the point...
Fig. 5: Visualising the representations learnt by the Model

cloud, as shown in Fig. 5B. In Fig. 3 we visualize the attention maps for various levels of point corruption and see that the model focuses on similar regions in all cases. An interesting observation is that the model can identify noisy points and not pay attention to them.

**TABLE IV:** Model Parameters, Size and Forward Pass time

| Method       | Params(M) | Size (MB) | Time (ms) |
|--------------|-----------|-----------|-----------|
| MVCNN (12 views) | 128.93    | 515.7     | 55.6      |
| MVCNN-SA     | 15.34     | 61.5      | 27.2      |
| PointNet     | 3.5       | 40        | 25.3      |
| PointNet++ (MSG) | 1.48      | 12        | 163.2     |
| PointCNN     | 0.6 [6]   | 6.9 [6]   | [6]       |
| PointTransformer | 1.09     | 4.4       | 23.3      |

**F. Time and Space Complexity**

While view-based methods achieve high performance, they are very computationally expensive and less space-efficient than point-based methods, as shown in Table. IV. Among the point-based methods, PointTransformer is a much smaller model with only 1.09 M parameters compared to other methods like PointNet, PointNet++ having 3.5M, and 1.48M parameters, respectively. Apart from the number of parameters, our method has significantly lower computational time as it replaces all convolutions with fully connected layers. This proves the efficiency of our model without compromising on performance.

**V. CONCLUSION**

In this paper, we propose a stand-alone self-attention model, PointTransformer, for efficient point cloud representation. Our method derives a point embedding and models complex relationships among the points to create region-specific group vectors. Evaluation on a real dataset - RoofN3D along with benchmark dataset - ModelNet40 demonstrates the effectiveness of our model. The detailed analysis of the model’s performance on various simulated point corruptions proves its robustness and suitability for real datasets. The model is highly space and memory-efficient when compared to other methods. Some details of our implementation can be revised for efficiency, e.g., incorporating faster methods to obtain k-nearest neighbors. The value of M and G can also be further experimented with to understand their relevance.

**REFERENCES**

[1] Zhifeng Wu, S. Song, A. Khosla, Fisher Yu, Linguang Zhang, Xiaoou Tang, and J. Xiao, “3d shapenets: A deep representation for volumetric shapes,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 1912–1920.

[2] A. X. Chang, T. Funkhouser, L. Guibas, P. Hanrathan, Q. Huang, Z. Li, S. Savarese, M. Savva, S. Song, H. Su, J. Xiao, L. Yi, and F. Yu, “ShapeNet: An Information-Rich 3D Model Repository,” Stanford University - Princeton University - Toyota Technological Institute at Chicago, Tech. Rep. [arXiv:1512.03012], [cs.GR], 2015.

[3] H. Su, S. Maji, E. Kalogerakis, and E. G. Learned-Miller, “Multi-view convolutional neural networks for 3d shape recognition,” in Proc. ICCV, 2015.

[4] C. R. Qi, H. Su, K. Mo, and L. J. Guibas, “Pointnet: Deep learning on point sets for 3d classification and segmentation,” CoRR, vol. abs/1612.00593, 2016. [Online]. Available: http://arxiv.org/abs/1612.00593

[5] C. R. Qi, L. Yi, H. Su, and L. J. Guibas, “Pointnet++: Deep hierarchical feature learning on point sets in a metric space,” in Advances in Neural Information Processing Systems 30. Curran Associates, Inc., 2017, pp. 5099–5108.

[6] Y. Li, R. Bu, M. Sun, and B. Chen, “Pointcnn,” CoRR, vol. abs/1801.07791, 2018. [Online]. Available: http://arxiv.org/abs/1801.07791

[7] S. Xie, S. Liu, Z. Chen, and Z. Tu, “Attentional shapecontextnet for point cloud recognition,” in 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, pp. 4606–4615.

[8] J. Lee, Y. Lee, J. Kim, A. R. Kosior, Y. Choi, and Y. W. Teh, “Pytorch implementation of set transformers,” https://github.com/juho-lee/set_transformer/issues/3, 2019.

[9] X. Liu, Z. Han, X. Wen, Y. Liu, and M. Zwicker, “L2G auto-encoder: Understanding point clouds by local-to-global reconstruction with hierarchical self-attention,” in Proceedings of the 27th ACM International Conference on Multimedia, MM 2019, Nice, France, October 21-25, 2019, ACM, 2019, pp. 989–997. [Online]. Available: https://doi.org/10.1145/3343031.3350950

[10] M. Gkeli and C. Ioannidis, “Automatic 3d reconstruction of buildings roof tops in densely urbanized areas,” ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XLII-4/W10, pp. 47–54, 2018. [Online]. Available: https://www.int-arch-photogramm-remote-sens-spatial-inf-sci.net/XLII-4-W10/2018/18/

[11] X. Zhang, A. Zang, G. Agam, and X. Chen, “Learning from synthetic models for roof style classification in point clouds,” in Proceedings of the 22Nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, ser. SIGSPATIAL ’14. New York, NY, USA: ACM, 2014, pp. 263–270. [Online]. Available: http://doi.acm.org/10.1145/2665310.2666407

[12] J. Castagno and E. Atkins, “Roof shape classification from lidar and satellite image data fusion using supervised learning,” Sensors, vol. 18, p. 3960, 11 2018.

[13] D. A. Shajahan, V. Nayel, and R. Muthuganapathy, “Roof classification from 3-d lidar point clouds using multiview cnn with self-attention,” IEEE Geoscience and Remote Sensing Letters, vol. 17, no. 8, pp. 1465–1469, 2020.

[14] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in Neural Information Processing Systems 30. Curran Associates, Inc., 2017, pp. 5998–6008. [Online]. Available: http://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf

[15] A. Wichmann, A. Agoub, and M. Kada, “Roof3d: Deep learning training data for 3d building reconstruction,” ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XLII-2, pp. 1191–1198, 2018. [Online]. Available: https://www.int-arch-photogramm-remote-sens-spatial-inf-sci.net/XLII-2/W5/11912018/18/

[16] S. Gupta and R. Bohare, “Project title,” https://github.com/sarthakTUM/roof3d, 2019.

[17] Y. Liu, B. Fan, G. Meng, J. Lu, S. Xiang, and C. Pan, “Densepoint: Learning densely contextual representation for efficient point cloud processing,” in The IEEE International Conference on Computer Vision (ICCV), October 2019.

[18] J. Li, B. M. Chen, and G. H. Lee, “So-net: Self-organizing network for point cloud analysis,” CoRR, vol. abs/1803.04249, 2018. [Online]. Available: http://arxiv.org/abs/1803.04249