Archaeological Textures Segmentation – A Pointnet based geometric textures detector

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Abstract

Geometric texturest segmentation it's a challenging 3D task, but it could be very useful to classify different objects which have some shapes and patterns in common in many fields of application, for example art and archaeology. In this article it's presented a system that aims to segment a 3D image detecting its geometric textures. This system works with point clouds, a set of data points in 3D space, and it's based on Pointnet, a unified architecture that directly takes point clouds as input and outputs either class labels for the entire input or per point segment/part labels for each point of the input.
Before feeding the Pointnet for segmentation, it has been necessary operate on the original dataset to make it compatible with the Pointnet itself. In this paper, it's firstly shown how the dataset was organized and converted, then it's presented and discussed test results analysis. The dataset is formed by images taken from SHREC'18 dataset which consists in 3D archaeological fragments.

Keywords: Geometric textures, patterns, point cloud, Pointnet, 3D images, relief patterns

1. Introduction

A peculiar chatacteristic behind relief pattern is that the style of this patterns does not depend on the overall structure of the shape; they are rather characterized by some regularity and repeatability across the surface so that they can be regarder as the 3D geometric equivalent of textures in 2D images. Starting from this property, the archaeological textures segmentation system presented in this work aims to detect, segment and thus classify differents patterns in a 3D image, taking as input points cloud, chiech are an important geometric data structure which rapresents a set of unorders points in the space. The point cloud has been choosed because the system presented in this paper it's based on Pointnet, a neural network that provides also a part segmentation system using points cloud. Pointnet part segmentation intends to recognize and segment different parts in various kind of objects: for example, given an airplane, using the Pointnet part segmentation system we'd like to obtain an annotation of an airplane different parts, like wings, fuselage, body, landing gear etc. The goal of this project is to test Pointnet segmentation power not in objects parts annotation, but in geometric relief patterns recognition and segmentation, using points cloud as input, not facets like in some related works [1]. In this arcticle a short description of Pointnet is presented; then, it's described the dataset used for test and its manipulation for compatibility with the network. Finally network settings, test and experiments results are shown.

2. Pointnet network

Pointnet [2] is a deep net architecture suitabe for consuming point sets in 3D; each point is rapresented by just three coordinates (x, y, z) ; however, more local or global features can be added for a deeper learning. In general, the input is a subset of points with three main properties: it's an unordered set of points; the points are from a space with a distance metric (Euclideian space), so it means that points are not isolated; finally, point sets are invariant to geometric trasformations. The Pointnet key is the use of a single symmetric function, max pooling; the network learns a set of optimization criteria that select informative points from the points cloud encoding the reason of their selection. In the final pointnet architecture leraning step, thee learnt optimal values are aggregated into a global descriptor to predict global point labels for shape segmentation. Definitely Pointnet is formed by three main layers:

- Symmetry function for unordered inputs: in order to make a model invariant to input permutation, the idea is to approximate a general function defined on a point set using a composition of multi-layer perceptron network and max pooling functions, achieving strong performaces.
- Local and Global Information Aggregation: The output from the above procedure generates a features vector; it's possibile to train an SVM or a multi-layer perceptron classifer on the shape global features for classification. For point segmentation it's required a combination of local and global knowledge: local information is obtained feeding back the global point cloud feature vector to per points features by concatenating the global feature with each of the point features. Then new per points features aware of both global and local information are extracted.
- Joint alignment network: all input are aligned to a canonical space before features extraction letting semantic labelling to be invariant if the point clouds undergoes certain geometric transformation such as a rigid transormation.

The architecture presented above allow the Pointnet 3D objects part segmentation, the functionality required and used by the system presented in this work. Given a 3D scan or mesh model, the task is to assign a part category to each point. Part segmentation is a part point classifier. Evaluation metric is mIoU (mean intersection over union). In general, since Poinnet learns a global shape signature for every given input point cloud, it's expected that geometrically similar shapes have similar global signature. It also should be noted that the per-point part labels are predicted based on the combination of per point features and the learnt global shape features. So, these two peculiarities guarantee robustness in part segmentation, on the other hand suggest an uniform dataset for relief patterns recognition, as shown below.

3. The Dataset

The original dataset used for experiments shown in this article is a subset of images selected from SHREC'18 dataset [3] . It consists in Matlab files, one for each image. A file contains vertices coordinates (points cloud), which form the image, facets and repective labels, which describe the ground truth. The labels refer to facets, not points; since Pointnet works with points, the new dataset actually used for tests has been obtained labelling vertices from the label of the facet to which they belong. Another problem with original dataset is its dimension: each image has a different number of point from one another; furthermore, Pointnet has been designed to work with 256, 512, 1024 or 2048 points, while the original dataset has images formed by a number of vertices ranging from 9037 to 99828. To solve this problem, each image, formed by labelled vertices, has been sampled in sub models of 256, 512, 1024 and 2048 points. Effectly, from each image belonging to the original dataset, four new dataset was obtained: the first with 256 points samples, the second with 512 points samples, the third with 1024 points samples and the fourth with 2048 points samples. Obviously, each point in new datasets is correctly labelled thanks to the first step described above. The points loss from the sub sampling procedure is not revelant for the purpose of the experiments.

1.1 *Dataset files and their meaning*

Archaeological Textures Segmentation, given a 3D image described by point cloud with its labels, generates a respective dataset from the image itself. This dataset consists in a set of sub samples. Each sample is described by three files everyone with a specific role in the computation and in the test execution:

- .ply files: "Polygon file format" files allows the visualization of the image.
- .seg files: they are simply the points labels.
- .pts files: these files contains only the coordinates of each point and are necessary after train in the test procedure.

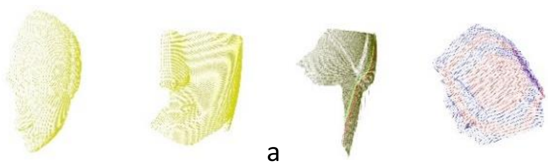
Once generated these files, the effective neural network input is obtained thanks to the .ply and .seg files: all the informations contained in these files are stored in two differents .h5 files, one for training and one for testing segmentaion, indispensable for Pointnet learning process. An .h5 file is a file which contains multidimensional arrays; these files are used for the manipulation of a large amount of data. The .h5 files generated by the system here presented contains the coordinates ('data') and the labels ('pid') of each point of each model obtained like exaplained above.

4. Experiments

Once the dataset has been generated, the network setting is necessary. Following the istructions given by Pointnet authors, a tensorflow model named “pointnet_archaeological_detection” has been created, for the implementation of a pointnet-like architecture for geometric textures recognition and segmentation. For testing, the dataset consisted in ten different images and twelve differents relief patterns. The number of distinct patterns for model varies from two up to five.
Each image has been sampled in sub-models formed by 256, 512, 1024 and 2048 points; the Pointnet has been tested over these different models using a batch size of 4 and a number of epochs equal to 100.
It has been demonstrated that this system works well with images divided in samples that presents a similar distribuition in the 3D space, while there are not desireble results for images sampled in models characterized by a very different distribuition. Furthermore, the partition using 512 points per sample works better, ensuring more accurate results.The table below summarizes test results. First five images obained a better segmentation then surfaces; this reults is explained by the bad sub sampling process of these models with respect to the other five. Moreover, it’s evident that a dataset consisting of 512 points objects allows better results.

	256 points	512 points	1024 points	2048 points
EgyptFace2	Acc: 54% IoU: 21%	Acc: 61% IoU: 41%	Acc: 30% IoU: 33%	Acc: 44% IoU: 24%
EgyptFaceDense	Acc: 47% IoU: 73%	Acc: 72% IoU: 80%	Acc: 46% IoU: 74%	Acc: 37% IoU: 50%
Eyebrow	Acc: 36% IoU: 50%	Acc: 72% IoU: 82%	Acc: 64% IoU: 72%	Acc: 35% IoU: 50%
face	Acc: 52% IoU: 76%	Acc: 94% IoU: 95%	Acc: 52% IoU: 76%	Acc: 52% IoU: 76%
face3	Acc: 55% IoU: 77%	Acc: 57% IoU: 63%	Acc: 48% IoU: 50%	Acc: 49% IoU: 51%
Surface1	Acc: 68% IoU: 84%	Acc: 31% IoU: 64%	Acc: 13% IoU: 51%	Acc: 67% IoU: 83%
Surface4	Acc: 42% IoU: 71%	Acc: 42% IoU: 71%	Acc: 40% IoU: 70%	Acc: 40% IoU: 70%
Surface5	Acc: 78% IoU: 61%	Acc: 78% IoU: 59%	Acc: 77% IoU: 53%	Acc: 43% IoU: 50%
Surface6	Acc: 23% IoU: 60%	Acc: 78% IoU: 50%	Acc: 0% IoU: 50%	Acc: 0% IoU: 50%
Surface7	Acc: 32% IoU: 70%	Acc: 38% IoU: 69%	Acc: 38% IoU: 69%	Acc: 0% IoU: 50%

Tabella 1: Experiments results



a

b

Figure 1: An example of original dataset models (a) and one good and one bad original dataset division (b).

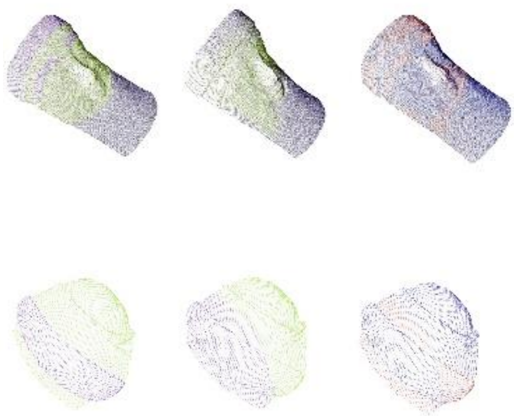


Figure 2: EgyptFaceDense and Eybrow GT, PRED and DIFF files. Diff files show differences between GT and PRED files.

5. Conclusion

In this article, a system for relief pattern detection and segmentation based on pointnet network has been presented[4]. It has been shown that it's possibile to split a point cloud object in a subset of objects defined by a smaller number of points and use these models to detect different geometric tesxtures in the original one. Improvements can be done, for example providing a more efficient splitting criteria in sub images definition or coherently adding more information to point clouds, trying to obtain more accuracy in segmentation process thanks to pointnet architecture.

References

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