Spherical Subsampling as a new Approach for Augmentation of 3D Point Cloud Data of biological Scans

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ABSTRACT

3D scans of real world objects are often represented by point clouds, creating XYZ-coordinates of individual scan points. However, unlike point clouds that are generated from CAD data, points generated from a real world scene lack information about their local context, making segmentation of the structural information contained in the data difficult.

Using neural networks (e.g. PointNet) has shown promising results. However, this approach is not well suited for scans of large areas of similar objects, like e.g. a wheat field, because of limitations of the input vector size of the neural network. In addition, point clouds are often unordered, further complicating processing. Since point clouds of biological objects often contain recurring features, we propose to subdivide the point cloud into locally neighboring subsets with a fixed number of points.

The collection of subsets can then be used to train neural networks. This approach preserves the original resolution of the point cloud while offering simple data augmentation concepts like creating a number of different subset collections from the same ground truth.

There are several advantages to this approach, like significantly simplifying the training phase, because a single, large annotated scan can be sufficient for training, utilizing the similarity of the instances of a plant in the field.

Keywords: Point Cloud, Semantic Segmentation, Neural Networks, Spherical Subsampling, 3D data augmentation.

1. INTRODUCTION

1.1 Problem statement

Processing 3D point data of plants with the purpose of e.g. plant phenotyping presents a unique set of challenges. When it comes to semantic segmentation of a single plant's scan into individual parts like leaves, fruit, etc. an analytic approach is normally very difficult, partly because the point data is not distributed evenly and the points lack neighborhood information, partly because a new algorithm needs to be developed every time an assumption the algorithm is based on changes. The problem is aggravated with multiple plants in close vicinity and color not being available for use in the segmentation process, for instance in a 3D scan of a wheat field. Recent advances in using a neural network (NN) like PointNet [1] for segmentation encouraged us to use NNs for segmentation of 3D point clouds of plants.
Using a NN requires choosing an input vector of a fixed size, and a large number of annotated samples of the same vector size as training data. Since the time required to train the network largely depends on the size of the vector, it is impractical to use e.g. the scan for an entire wheat field because the NN would be impractically large. Also detailed annotation of thousands of scans of entire wheat fields with thousands of plants each is a paramount task. Wang et al. [2] propose to downsample the data to reduce the vector size,

but this severely affects data resolution and quality. Also, one needs to keep in mind that the point cloud data set is mathematically a set without inherent order, so unless assumptions can be made regarding the way the point cloud was generated, an algorithm should compute comparable results on all permutations of the point cloud data set.

1.2 Approach: Spherical SubSampling (SSS)

We propose an alternative approach, i.e. to subsample the large point cloud into spheres containing local subsets. The idea of subsampling a scene into spheres was used by Borgmann et al. [3] for detection of pedestrians in autonomous driving applications. Utilizing the fact that the data set of a plant field contains thousands of copies of similar – but not identical – instances of an object of the same kind, we suggest subsampling the original data set into spheres around random seed points, which will all contain similar content. Using a sphere greatly simplifies the calculation of the Euclidian distance of each point of the point set to the seed point at the center of the sphere. Each sphere will contain all points of the original data set within the radius, much like a puzzle piece contains a part of a larger image. So each sphere can be viewed individually as a scan of part of a scene, and if the original scan was annotated, the points in the sphere inherit the annotation and retain the full information of the original scan. By removing the points contained in a sphere from the dataset and iteratively repeating the process, a large number of annotated sample vectors can be generated. Having a considerably smaller vector size than the original data set, this reduces the time required to train the NN while at the same time generating thousands of separate samples for training. Also, since the spheres are created around random seed points, the same original data set can be processed multiple times, each time creating a new, unique set of spheres different from the ones generated previously on the same data set. The approach offers a number of straightforward parameters to control the behavior of the subsampling algorithm, allowing the user to adapt the performance to the problem at hand.

2. THE ALGORITHM: SSS

2.1 Basic concept

SSS extracts subsets of points out of a point cloud based on their geometric relations. Initially, a randomly chosen point acts as the first sphere's center point. Then, all points within a given Euclidian distance of this point are stored as a separate sub-sphere entity. The points of this sub-sphere are subsequently deleted from the original point cloud to assure termination of the algorithm and the process is repeated until a threshold is reached or all data points have been processed.

Extending this basic sub-sampling algorithm, there are many options for variations e.g. for data augmentation. In addition, further approaches with a less random center selection in order to subsample the dataset more systematically or using other parametrizations like restraints regarding the number of points per sub-sphere are explored.

2.2 Example SSS Variation: nested double Spheres

In this variation of SSS not all of the points within an extracted sub-sphere are removed from the original point cloud. Instead, only points within a smaller radius around the same given center point are deleted in each iteration. Thus, a certain partition of data points remains in the original point cloud despite being also part of an already extracted sub-sphere. These data points remain available to become part of another sub-sphere as the algorithm further proceeds, which means that some points are extracted multiple times, but in different and unique local environments. It also means that this variation of the algorithm can create overlapping spheres as opposed to the unmodified version, which only creates disjunctive spheres by design. This allows SSS to artificially increase the volume of a dataset, maintaining object details in each sphere.

```
Algorithm 1: pseudo code framework for SSS
Choose arbitrary point as first c ⊆ D;
while n(D) > T do
    Select all points ⊆ D with distance to c ≤ outer_r as S;
    if n(S) ≥ min_n then
        if n(S) < N then
            point padding until n(S) = N;
        else if n(S) > N then
            point removal until n(S) = N;
        end
        Calculate additional feature values for all points ⊆ S;
        Store S with features for further processing;
    end
    Select all points ⊆ S with distance to c ≤ inner_r as inner_sphere;
    Remove all points ⊆ inner_sphere from D ;
    Remove all points ⊆ inner_sphere from S;
    if n(S) ≤ t then
        Assign center c_new out of remaining points in S;
    else
        Assign random point ⊆ D as c_new;
    end
    Continue while loop with c_new and smaller D;
end
```

Figure 1: Pseudo code of algorithm for SSS with nested double spheres

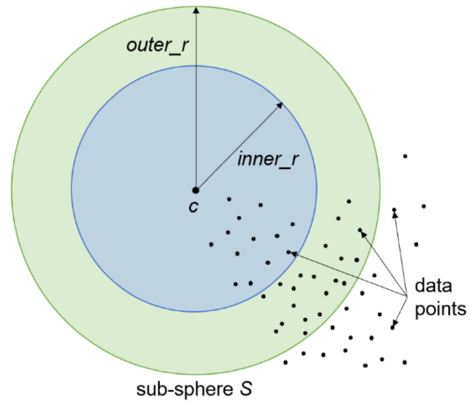

Figure 2: Example illustration of one nested double sphere

Based on this variation of SSS several experiments ensured that the sub-sampling procedure does accurately represent the original dataset in terms of target class distribution and general feature representation. Since all resulting sub-spheres should contain the same number of points N, we implemented optional point padding and deletion procedures.

The resulting sub-spheres provide a foundation for further processing steps. Since the spheres consist of a fixed number of data points, they can be used directly as input for training or inference of NNs. Moreover, multiple data augmentation applications are possible: the use of the spheres as a basis for super-points, sampling datasets multiple times, generation of additional features like a coordinate transformation relative to the center to facilitate location invariant training of the NN, or further augmentations like point dropout, rotation, noise, etc.

3. RESULTS

3.1 Wheat Field Segments representative for homogenous biological Data

The point cloud data of a wheat field used in this paper was created using a Field Scanalyzer [4], which uses the sheet-of-light triangulation principle. A scan of one of the field segments that were used in our experiments is displayed in Figure 3. The core metric used for evaluation of the NNs predictive performance used is mean intersection over union (mIoU).

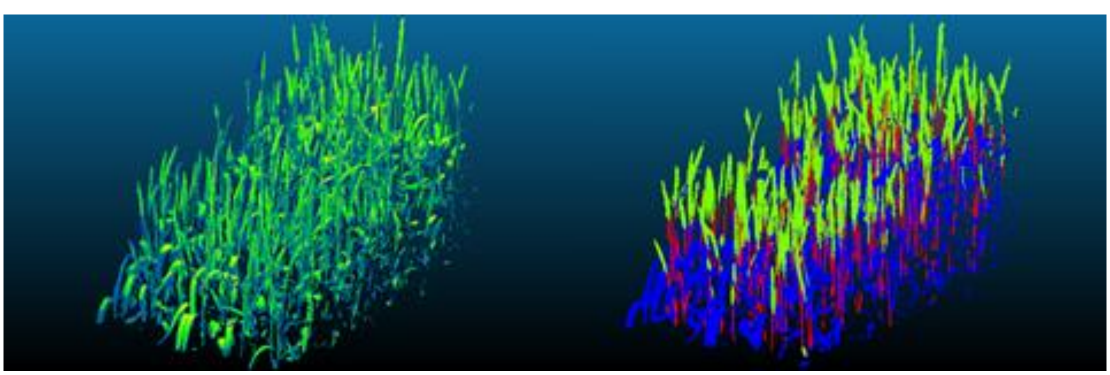

Figure 3: Raw (L) and labeled point cloud (R) with color-encoded target classes: ear (green), stem (red), rest (blue)

3.2 Initial Results applying SSS

Experiments with PointNet++ [5] showed that models trained with data sampled using basic SSS outperformed their counterparts trained with data of grid based, e.g. oct-tree. SSS improves mIoU by an average of ~7%. Furthermore, for use-cases where only limited data is available SSS simplifies artificially increasing the training data, which has led to further improvements in our experiments. Using the nested double sphere approach has shown promising results in form of additional prediction performance increases of 2-8% mIoU. This proved to be especially effective, when only very limited quantities of data were used for training. The NNs trained with sub-spheres proved to be robust in transfer learning tasks and generalized well to other wheat segments with different phenotypes.

4. CONCLUSION

SSS provides data formatting suitable directly for training of NNs for semantic plant segmentation. One wheat field segment (as seen in Figure 3) was sufficient for training a NN that can generalize well to other field sections – even if they contain different phenotypes of wheat. The concept of reusing data points in different local environments potentially enables the application of NNs even if the available amount of labeled data is insufficient when using traditional data preparation methods. Due to its simplicity and reliance on spheres containing similar content, SSS has the potential to perform real-time sub-sampling for classification tasks in the field, e.g. in robotic applications.

As next steps, we plan to investigate the influence of all parameters and aim to simplify our approach to make it universally usable without prior dataset specific parametrization. Optimizing parameters and evaluating a dynamic version of the algorithm that creates spheres of varying radii but equal cardinality will potentially further improve our method and thus contribute to the practicability of using NNs for 3D semantic segmentation in plant phenotyping research.

DATA AVAILABILITY STATEMENT

The 3D point cloud data of a wheat field used in this paper was kindly provided by Rothamsted Research, Hertfordshire, UK.

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