Fast-Point-Feature Histograms for Plant Organs Classification

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***Abstract*— In this paper, we shortly summarize our key findings and detail our implementation for the fast-point-feature histogram descriptors of three-dimensional point clouds. Our approach uses basically the pipeline outlined in the lecture and reaches for the classification of berries and stems on the provided test set an average precision of 99.3% and recall 78.9%, respectively.**

I. INTRODUCTION

In this paper, we report our findings regarding the fast-point-feature histogram descriptors of three-dimensional point clouds. We used in principle the outlined approach of the lecture and implemented all needed data structures and processing methods to classify three-dimensional point clouds by applying the following steps:

1) Computation of point normals,
2) Computation of Darboux Frame and features needed for point-feature histogram descriptors,
3) Building the Histogram descriptor using fast-point-feature histogram,
4) Classification of point clouds into berries and stems using SVM^{Light}
5) Region Merging algorithm for post processing of labeled point clouds

In the next section, we detail the specific parameters used in this pipeline and outline any additional insights we got while implementing and evaluating our approach. In the following section, we summarize our experimental results using these parameters on the provided test dataset. The last section discusses our results and describes some insights we got from our experiments.

II. APPROACH

In this section, we briefly summarize the parameters of our approach and describe notable improvements we found to work in practice.

A. Kd-tree

We implemented the standard kd-tree implementation from the literature. We used a K dimensions $k = 3$ for storage of the point clouds.

B. Normal Estimation

We implemented a normal estimation for the point cloud based on the eigen values computed from covariance matrix using the radius $r_N = 1.5\,mm$.

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C. Fast-Point-Feature Histogram

We used a Point-Feature Histogram(PFH) with $r = 5\,mm$ and 62 bins where $binsize = 0.1\,m$.First we extracted the nearest neighbor points for each query point using kd-tree structure.Second,we computed the Darboux frame and the , and features used the equations from the lecture.Then,we computed the simplified PFH which is then used in the Fast-Point-Feature Histogram(FPFH) as illustrated in the lecture.

D. SVM Light

We used the SVM^{Light} with the default parameters for classification.We used a linear kernel method with a biased hyperplane option and the rest of the options can be checked in the SVM^{Light} documentation.

E. Post Processing using Region Growing

The postprocessing is done after classifying the 3D point clouds using a region growing algorithm that merge the points of a smaller region to a bigger region in the direct neighborhoods as explained in the research paper and the lecture to enhance the classification output

III. EVALUATION

Our approach with the described parameters and training procedure was applied to the training data, where we reached a training error of 4.48%. The complete approach with feature computation and classification achieved an average precision of 99.3%, recall 78.9%, and accuracy 94% for berries and stems, respectively.

For further improvements, we would like to investigate to improve the classification by optimizing R_N and R_H