Keypoint Cascade Voting for Point Cloud Based 6DoF Pose Estimation

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Abstract

We propose a novel keypoint voting 6DoF object pose estimation method, which takes pure unordered point cloud geometry as input without RGB information. The proposed cascaded keypoint voting method, called RCVPose3D, is based upon a novel architecture which separates the task of semantic segmentation from that of keypoint regression, thereby increasing the effectiveness of both and improving the ultimate performance. The method also introduces a pairwise constraint in between different keypoints to the loss function when regressing the quantity for keypoint estimation, which is shown to be effective, as well as a novel Voter Confident Score which enhances both the learning and inference stages. Our proposed RCVPose3D achieves state-of-the-art performance on the Occlusion LINEMOD (74.5%) and YCB-Video (96.9%) datasets, outperforming existing pure RGB and RGB-D based methods, as well as being competitive with RGB plus point cloud methods.

1. Introduction

Accurate, robust and efficient six-degree-of-freedom pose estimation (6DoF PE) is an enabling technology for applications such as augmented/virtual reality [21, 67], robotic grasping [32], autonomous driving [24], and so forth. 6DoF PE aims to determine the rigid transformation (comprising the 3DoF translation and 3DoF rotation) of an object of known geometry and/or appearance within a captured scene. This problem has been intensively investigated by the research community, initially using classical analytical approaches [1, 48, 36], and more recently exploiting the advent of machine learning (ML) methods [21, 67, 66, 13].

A number of recent leading ML approaches [42, 20, 66] have been proposed based on keypoint voting, in which the 3D scene coordinates of specific keypoints defined within an object’s reference frame, are voted on and accumulated independently for each image pixel. The accuracy with which Convolutional Neural Networks (CNNs) are able to regress geometric information about the locations of key-
points within a scene is a main reason for the effectiveness of these approaches, and a number of variations have emerged which take both pure RGB [41, 55, 58, 68, 69, 28, 67, 62], as well as RGB-D [66, 50, 18, 20] data as input.

Whereas many classical approaches process 6DoF PE in 3D point clouds [48, 53, 36], the unordered nature of point clouds presents a challenge to ML approaches for which the ordering of the data matters. In particular, consecutive points in the point clouds may not be in the same neighborhood and due to the lack of proximity information, they cannot be fed to CNNs or in general Artificial Neural Network (ANN), unlike a pixel-ordered RGB or RGB-D image. Two approaches that have been proposed that impose order on the 3D data are voxel-based [18, 71, 37], in which the point cloud is cast to a 3D grid structure, and view-based, which resamples the data from a set of directions along the view sphere [21, 69, 22]. A further alternative has been to consider ML architectures that process point clouds independent of their ordering [3, 11, 15, 38, 35, 44, 51, 61]. The PointNet series [43, 45] has emerged as the most successful such approach, which makes use of a number of trainable symmetric functions which are invariant to point ordering.

In this work, we apply the powerful keypoint voting approach, taking pure 3D point cloud data as input. One challenge is a limitation to the size of the input point cloud. Whereas in processing conventional image-structured data (RGB, or RGB-D), the nature of CNNs can accommodate large input images, PointNet and other non-CNN based point cloud methods have a much stricter limit to the size of the input image. Further, in many realistic scenes, the object of interest comprises a relatively small percentage (e.g. 5% to 15%) of the image [21, 67], so that the majority of the input data is considered background or clutter.

To address this, we have developed a novel keypoint voting architecture based on RCVPose [66] called RCVPose3D, which partitions the segmentation and regression tasks. In previous work, segmentation and regression were trained and executed in parallel, whereas in the proposed architecture, which we call cascaded keypoint voting, these tasks are trained independently and separately, and are executed end-to-end at inference. This novel architecture has two main benefits: First, training segmentation and regression separately increases the accuracy of each of these tasks, as they each have their own independent dedicated network. The second benefit is at inference, where background points are initially filtered out by the segmentation task, so that only foreground points are passed to regression. This not only reduces the computational expense of regression, but also increases voting effectiveness, as background points are filtered out. Some sample results are shown in Fig. 1.

The main contributions of this work are as follows:

- A novel cascade architecture for keypoint voting based 6DoF PE that partitions the segmentation and regression tasks. This improves training of these two independent tasks, and ultimately increases performance. Based on this architecture, we introduce RCVPose3D, which is the first variation of keypoint voting based 6DoF PE that takes pure 3D point cloud data as input.

- A novel loss function that considers the Euclidean distance between pairs of simultaneously regressed keypoints as a geometric constraint, and improves keypoint estimation accuracy.

- A novel evaluation score based on the voting space resolution. This score reduces the computational expense of training by evaluating the voter regression network, and culling certain points before voting, thereby accelerating hyperparameter tuning.

RCVPose3D has been thoroughly evaluated and compared against other state-of-the-art (SOTA) methods, and a series of ablation studies have been performed to characterize its effectiveness. The code is available to the public at https://github.com/aaronWool/rcvpose3d.

2. Related Work

This section reviews previous 6DoF PE work. Tab. 1 lists an overview of these works, classified by their input data modes of RGB, RGB-D, or 3D (i.e., point cloud).

2.1. 6DoF PE from RGB and RGB-D Images

Advances in 6DoF PE have been facilitated by the establishment of datasets such as LINEMOD [21] and YCB-Video [67], which include pose information of a variety of objects for a large number of RGB-D scenes under various cluttered and occluded conditions. The majority of ML-based methods have used pure RGB data images [55, 28, 41, 69, 58, 68, 62], while some have also used the depth (i.e., D) information provided by range sensors such as Microsoft Kinect [67, 18, 50]. For all RGB and RGB-D methods, the input images are multi-channel (i.e., 3- or 4-channel) 2D arrays with ordered pixel grids. These images are naturally handled by CNNs. OP-Net [30] is notable in that it processes only the D field of an RGB-D image, making use of the image ordering in a YOLO-like grid.

2.2. 6DoF PE from 3D Point Clouds

With the progress in the development and availability of 3D acquisition sensors, point clouds became popular in pose estimation [20, 19, 13, 18] and other computer vision applications [71]. Using a point cloud, surface and geometric constraints and characteristics of a rigid object are better exploited and can improve pose estimation in certain situations [20], such as in industrial applications where the
Geometry data has also been recently used by some RGB-D works to accept as input unordered point cloud data. Scanned parts are radiometrically textureless [32, 23]. Active range sensors, such as LiDaR, are also beneficial in applications such as autonomous driving [71, 49], where ambient lighting conditions can confound passive 2D sensors.

In some methods [20, 19, 60], the RGB data serves as the input to a CNN, and the 3D geometry data only enhances feature embedding. These methods have better performance compared to pure RGB methods, but they have never studied the impact of RGB and geometry separately. Geometry data has also been recently used by some RGB-D methods [69, 28, 67, 62] by applying pose refinement, such as ICP [2], as a post-processing step.

Prior to the advent of ML in computer vision, many research works were dedicated to the design of effective 3D feature descriptors for 6DoF PE and many other applications. This includes a large variety of 3D feature descriptors such as Point Signatures [5], Spin Images [27], and Point Pair Features (PPF) [9]. For a thorough summary of classical 3D feature descriptors, see [17]. While the classical literature was replete with 6DoF PE solutions using point cloud data [16], there have been very few such ML-based works on 6DoF PE. An exception is BaseNet [13], which makes use of PointNet for 3D feature extraction.

Following PointNet series [43, 45], several more recent ML methods designed for 3D point cloud/mesh were introduced. Point Transformer [70] adapts the transformer [59] to point clouds using vector attention. DGCNN [64] uses topology-based graph convolutions to extract 3D features. SubdivNet [25] investigate the properties of mesh and design a descriptor for it. Lastly, PPFNet [7] embeds the classic PPF into a CNN to encode features.

In addition to those methods that apply ICP for post-processing, there have been a few 6DoF PE methods that have made further use of 3D point cloud data. PVN3D [20] fuses PointNet features with 2D convolution features to estimate keypoints, the object center, and a semantic mask with a multi-task network loss all together. A least square fitting gives the final pose estimation. In PointVoteNet [18] the geometry and RGB information is voxelized and an anchor box is used to localize the target object location. The final pose is given by an offset clustering. While some recent works combine classic hand-crafted 3D descriptors such as PPF [7, 6] in the feature extraction stage, others use a topology graph [64, 34, 63] as a 3D feature descriptor instead of pure Euclidean local geometry.

### 3. Background: Keypoint Voting Framework

Classical voting methods such as Hough [10], RANSAC [12] Pose clustering [40] and Geometric Hashing [33] proved to be robust and highly effective. The accumulator space where all votes are aggregated independently, effectively filters out noise and background clutter, yielding an accurate estimation. With the advent of neural networks, voting techniques have gained more popularity. Recent works such as PVNet [42], PVN3D [20], and RCVPose [66] that exhibit leading SOTA performance, have merged voting-based methods, which are well established in the classical literature [61, 54], with recent ML-based keypoint estimation approaches.

The general keypoint voting architecture first proposed in PVNet for RGB input, and then modified in PVN3D and RCVPose for RGB-D input, is shown in Fig. 2a. We describe here the common elements and some variations of this architecture, and in Sec. 4 we introduce a number of modifications to accept as input unordered point cloud data.

The framework aims to estimate the 3D coordinates of a number of keypoints for an object in a scene. The keypoints themselves are simply a set of 3D points defined within the object-centric reference frame, and which therefore transform rigidly with the object. There is no requirement that all (or indeed even any) keypoints be visible in a scene, the main criterion being that there are at least 3 keypoints per object, and that they are sufficiently separated so as to allow for accurate recovery of the object pose. Keypoints have been defined in a variety of ways, including the object bounding box corners [39, 46, 56], farthest point sampling [42, 20], and disperse sampling [66].

As shown in Fig. 2a, the framework passes input image $I$ through an encoder-decoder network $ED_{SM}$. In PVNet, $I$ was an RGB image, and $ED_{SM}$ was based on a ResNet-18 backbone. RCVPose used ResNet-152 for $ED_{SM}$ for the RGB mode of an RGB-D input image $I$, with D being

| Method          | Publication Date | Data Mode |
|-----------------|------------------|-----------|
| Tekin et al. [55] | 2017             | ✓         |
| SSD-6D [28]     | 2017             | ✓         |
| Pix2Pose [41]   | 2019             | ✓         |
| DPOD [69]       | 2019             | ✓         |
| Trabelsi et al. [58] | 2021   | ✓         |
| Dsc-posenet [68] | 2021             | ✓         |
| GDR-Net [62]    | 2021             | ✓         |
| PoseCNN [67]    | 2017             | ✓ ✓       |
| Tian et al. [57] | 2020             | ✓ ✓       |
| StablePose [50] | 2021             | ✓ ✓       |
| SO-Pose [8]     | 2021             | ✓ ✓       |
| PVN3D [20]      | 2019             | ✓ ✓ ✓     |
| DenseFusion [60] | 2019             | ✓ ✓ ✓     |
| PointVoteNet [18] | 2020         | ✓ ✓ ✓     |
| FFB6D [19]      | 2019             | ✓ ✓ ✓     |
| RCVPose [66]    | 2021             | ✓ ✓ ✓     |
| OP-Net [31]     | 2019             | ✓         |
| BaseNet [13]    | 2020             | ✓         |
| RCVPose3D       | 2022             | ✓         |

Table 1: Methods with various input data modes
then fused and merged, and fed to the decoder stage. The output latent spaces from these two parallel branches were used exclusively within the loss function and only during training. In PVN3D, \( I \) was RGB-D, and there were two parallel encoder branches, with ResNet-34 applied to the RGB mode, and PointNet++ applied to the D mode. The output latent spaces from these two parallel branches were then fused and merged, and fed to the decoder stage.

The output of \( ED_{SM} \) are two tensors \( S \) and \( M \), both of which have the same \( W \times H \) spatial dimensions as input image \( I \). Segmentation mask \( S \) indicates to which (if any) object class each pixel belongs.

Tensor \( M \) contains the values of the regressed quantities for each pixel, that are aggregated to localize keypoints in the subsequent voting stage. In PVNet, \( M \) contains a set of 2D vectors for each pixel, that point in the direction of each keypoint. The subsequent voting module \( V \) integrates the intersections of all such vectors in a 2D accumulator space, the peaks of which indicate the locations of keypoints (i.e., vector voting). In PVN3D, \( M \) contains a set of 3D offsets, which translate the 3D coordinate of each pixel to vote for each keypoint within a 3D accumulator space (i.e., offset voting). In RCVPose, \( M \) contains a set of 1D values that indicate the Euclidean distance between each pixel and each keypoint. A set of spheres with radii equal to the values in \( M \) for each pixel, are rendered within a 3D accumulator space, and the peaks at intersections of the sphere surfaces determine the keypoint locations (i.e., emphyral voting).

The output of voting module \( V \) is tensor \( T \), comprising \( K \) estimated keypoints for each of the \( C \) objects. While segmentation provides a mechanism to handle multiple objects, in order to increase accuracy, in practice all of PVNet, PVN3D and RCVPose consider only a single object class per network, i.e. \( C = 1 \). The \( K \geq 3 \) estimated keypoint scene coordinates, along with their corresponding canonical object-frame coordinates, are passed into pose module \( P \) to estimate the object 6DoF pose \( P \). For the purely 2D keypoint scene coordinates of PVNet, a RANSAC-based Perspective-n-Point (PnP) routine is used to recover the transformation, whereas for the 3D keypoint scene coordinates of PVN3D and RCVPose, a least squares fitting between two 3D point sets can be applied. Both PVN3D and RCVPose also refine the pose estimate further with a few ICP iterations, using a larger sample of 3D scene point data.

4. Proposed Cascade Approach: RCVPose3D

In this work, we propose a novel keypoint-based 6DoF PE method to estimate the pose of an object from pure point cloud data. The method regresses of the radius voting quantity of RCVPose \([66]\), which has been recently proposed. The method combines three main aspects, the first of which is the separation of the semantic segmentation and pose estimation encoder-decoder networks, which are arranged in a cascade architecture (Sec. 4.1). The second is a novel loss function that considers the pairwise geometric constraints between simultaneously estimated keypoints (Sec. 4.3). The third aspect is a novel score function specific to voting methods, that facilitates training (Sec. 4.4). In the following subsections, we describe these aspects in detail.

4.1. Cascade Architecture

The proposed cascade architecture, shown in Fig. 2b, contains similar processing elements as the existing parallel architecture of Fig. 2a, albeit in a different arrangement. The main difference is that the segmentation and regression encoder-decoder network \( ED_{SM} \) of the parallel architecture, has been decoupled in the cascade architecture into two distinct networks, \( ED_S \) and \( ED_M \). In cascade, the point cloud is first segmented prior to being passed to the regression stage. As shown in the figure, input point cloud \( I \) first passes through the (now independent) encoder-decoder network \( ED_S \), which results in segmentation mask \( S \). Only the filtered foreground points from \( S \) are then subsequently passed to regression network \( ED_M \), resulting in tensor \( M \) which is then passed to the subsequent voting module \( V \).

This new architecture has the advantage that each network \( ED_S \) and \( ED_M \) will learn their respective patterns independently, rather than training them jointly in a multitask fashion. This may seem counter-intuitive, as the essence of the popular multitask learning approach is to benefit from the interaction that occurs when training complementary tasks simultaneously. The key, however, is that multitask learning is mainly beneficial when the tasks contain correlated information that reinforces the learning process \([65, 4, 52]\). Our experiments (see Sec. 6.1) indicate that segmentation and keypoint regression are sufficiently...
defined as the radial pair difference between the GT radial values from a point $p_m$ to keypoints $k_i$ and $k_j$. Estimate $\Delta_{mij}$ of $\Delta_{mij}$ is then formulated as:

$$\hat{\Delta}_{mij} = |\hat{r}_{mi} - \hat{r}_{mj}| = |r_{mi} + \epsilon_{mi} - (r_{mj} + \epsilon_{mj})| \leq |r_{mi} - r_{mj}| + |\epsilon_{mi} - \epsilon_{mj}|$$

(2)

This is an expression of the triangle inequality, which has been applied previously to improve efficiency in nearest neighbor search [14]. The radial pair difference is complementary to the magnitude of the residual used in the unary $L_c$ loss. If $\hat{r}_{mi}$ and $\hat{r}_{mj}$ are both either underestimates or overestimates of their respective GT values (i.e. $\text{sign} (\epsilon_{mi}) = \text{sign} (\epsilon_{mj})$) then $|\epsilon_{mi} - \epsilon_{mj}| < \max(|\epsilon_{mi}|, |\epsilon_{mj}|)$, and the residual magnitude dominates. Alternately, if $\hat{r}_{mi}$ and $\hat{r}_{mj}$ fall on opposite sides of their respective GT values, then $\text{sign} (\epsilon_{mi}) = -\text{sign} (\epsilon_{mj})$, and $|\epsilon_{mi} - \epsilon_{mj}| \geq \max(|\epsilon_{mi}|, |\epsilon_{mj}|)$. In this case, the radial pair difference of Eq. 2 will exceed the residual magnitude.

We have exploited this by encapsulating Eq. 2 into the following loss term, which we call the Radial Pair Loss:

$$L_P = \frac{2}{M \times K(K-1)} \sum_{m=1}^{M} \sum_{i=1}^{K} \sum_{j=i+1}^{K} SL_1(|\Delta_{mij} - \hat{\Delta}_{mij}|)$$

(3)

The $L_P$ can be used during the whole training process, but it can be delicate at the initial stage. The exact same residuals in between different radii for different keypoints can exist in the initial random output. It does become dominant at later epochs, when the regression network training to be closer to fully convergence (i.e. the outputs approach groundtruth (GT) radii values) by enforcing the constraint on inter-keypoints distances. Our experiments (see Sec. 6.4) supports this premise and shows the significant impact of $L_P$ on both accuracy and training time.

4.4. Voter Confidence Score

In the literature, two classic metrics have emerged and are commonly used to evaluate the overall performance on the 6DoF PE datasets: ADD(S) [21] for LMO, and ADD-S AUC [67] and ADD(S) AUC for YCB. We also introduce a new Vote Confidence Score (VCS) for the evaluation of the radii estimation, prior to the voting stage.

ADD(S) measures the average distance for asymmetric objects, and the minimum distance for symmetric objects, between points of the object transformed with GT pose and the object transformed with the estimated pose. If the distance is within 10% of the object diameter threshold, then the estimated pose is considered to be correct.

ADD(S) AUC is based on ADD(S). It creates a curve by plotting different thresholds against ADD(s) accuracy scores. The accuracy score of AUC is therefore given by the area underneath the curve.
**ADD-S AUC** is similar to ADD(S) AUC, except it uses ADD-S only for all objects, with the measurement based on minimum point distances.

Here we define **VCS** as a measure of each estimated voters’ confidence level from the regression network. VCS is formulated based on the voting space resolution. For a voting space resolution (e.g., edge length of a cubic voxel) of \( \rho \), a vote is considered to be correct if the absolute error between the GT and estimated value is less than or equal to \( \rho \). The confidence score is then the ratio of correct to total votes. This score can estimate the performance of the voting regression network, even before votes are cast in accumulator space, and can accelerate hyperparameter grid search. For radii voting specifically, VCS is defined as:

\[
VCS = \frac{M'}{M}
\]

where \( M \) is the number of votes and \( M' \) is the number of correct radii votes when \( \epsilon_{m,i} = |\hat{r}_{m,i} - \hat{r}_{m,i}| \leq \rho \). The voting space will apparently be more confident with sharper peaks, when VCS is higher, and keypoint location will thus be more accurate (see Sec. 6.4).

### 5. Experiments

We evaluate the performance of our proposed RCVPose3D, and compare it with the best performing 6DoF PE methods on the two challenging 6DoF datasets that are commonly used in related SOTA work [42, 20].

#### 5.1. Datasets

**Occlusion LINEMOD** [21] (LMO) is an extension of the LINEMOD dataset, comprising 1213 annotated RGB-D images of 9 classes of object, with GT pose and semantic labels. LMO is extremely challenging, not only because the objects within the scene are heavily occluded but also because it is purely for testing purposes, the convention being to train on the original LINEMOD dataset, which only comprises non-occluded objects.

**YCB-Video** (YCB), is a video-based 6DoF pose dataset, initially proposed by PoseCNN [67], which was the first CNN for 6DoF PE. YCB contains 130K frames extracted from 92 videos, with RGB images, depth maps, and GT poses and semantic masks provided for 21 classes of objects. The challenge of YCB is that some frames are blurred and include occluded objects. We follow previous works [42, 20, 66] and use a train/test split of 85%/15%.

#### 5.2. Experimental Setup

To generate the 3D data, we use the camera intrinsic parameters to transform the depth maps into point clouds. Each point cloud is then downsampled to contain a total of \( N = 2^{15} \) points, which is close to the limit that our GPU could accommodate for a reasonable batch size of eight. Each point cloud is then recentered based on its bounding box, and normalized based on its maximum point value.

During training, the segmentation network inputs \( N \) points and estimates a semantic label for each point, indicating which object it falls on (if any). The segmentation output is randomly downsampled based on the estimated label probabilities, to comprise \( M \leq 1024 \) foreground points. The input of the regression network is the \( M \) foreground points, all of which have the same semantic label and thus fall on the surface of the object of interest. When training, these points are selected by applying the GT segmentation mask of the scene, and randomly downsampling the resulting foreground points to total \( M \) points.

At inference, the regression network estimates \( j = 3 \) keypoints’ radii simultaneously [66]. The output of the regression network is size \( M \times 3 \), comprising a radius from each input object point to all 3 keypoints.

The segmentation network’s loss function uses a standard Binary Cross Entropy (BCE) Loss \( L_{bce} \), whereas the regression network uses a combination of traditional Smooth L1 Loss on the radii residuals \( L_r \) (Eq. 1), and Radial Pair Loss \( L_p \) (Eq. 3). The regression loss is then:

\[
L_r = \alpha L_r + \beta L_p
\]

where \( \alpha \) and \( \beta \) are weights that are adjusted during the training as follows: During the first 100 epochs, we set \( \alpha = 0.8 \) and \( \beta = 0.2 \) so that the network learns to approach the actual radii values with minor assistance from the radial pair constraint. For the remaining 150 epochs, \( \alpha \) and \( \beta \) are adjusted to \( \alpha = 0.2, \beta = 0.8 \) for fine-tuning when \( L_r \) has mostly converged and \( L_p \) dominates.

The Adam [29] optimizer is used for both networks during training. The initial learning rate is set to \( 1e^{-4} \) and reduces \( \times 0.1 \) for every 50 epochs. We train the networks with a batch size of 8 for segmentation and 32 for regression on three RTX6000 GPUs.

#### 5.3. Performance Evaluation

To our knowledge, BaseNet [13] is the only other ML-based 6DoF PE method that inputs unordered point cloud data. OP-Net [32] does take pure depth data as input, although they use row-column image ordering using a YOLO-style [47] 2D grid decomposition, on a less common dataset. In addition to BaseNet, we also compare RCVPose3D with SOTA RGB and RGB-D methods. Two classic metrics are used to evaluate the overall performance of RCVPose3D. ADD(S) [21] for LMO, and ADD-S AUC [67] and ADD(S) AUC for YCB. Our experiments show that RCVPose3D is competitive with these other methods, even though it does not make use of any RGB information.
Table 2: LMO and YCB average accuracy results.

As shown in Tab. 2, on YCB, RCVPose3D performs better than all pure RGB methods. Its performance is especially relatively strong on objects such as wood block (+3% better) and mug (+1.7% better) which have a uniform color (see Supp. Mat.). RCVPose3D also outperforms all other SOTA methods with the relatively strict ADD(S) AUC metric, both with and without ICP refinement. It performs second best with the ADD-S AUC metric, approaching RCVPose [66] within a small margin (−0.6%).

On LMO, RCVPose3D again outperforms all SOTA methods that use RGB data. Similar to YCB, it estimates a better pose on objects with poor radiometric texture (almost uniform color) such as eggbox and can. It outperforms RCVPose by +3.4% for can (see Supp. Mat.). Compared to all methods, RCVPose3D is the second-best with on average only −0.6% less than PointVoteNet [18] which inputs both point cloud and RGB data (see Tab. 2).

Overall, RCVPose3D is the best performing metric for 6DoF PE on pure point cloud geometry. It also outperforms all methods that input pure RGB data. Finally, it is competitive with all other RGB-D/RGB+3D 6DoF PE methods, ranking either best or second best for different datasets and metrics.

6. Ablation Studies

We executed a series of experiments to characterize the benefits of the various novel elements of RCVPose3D using the common framework presented in Sec. 4. In particular, we characterized the impact of the cascade architecture and the Radial Pair Loss. We also compared the relative effectiveness of different backend 3D feature extractors. These tests were all executed on the complete LMO dataset.

6.1. Parallel vs. Cascade, and Radial Pair Loss

A set of experiments were executed to isolate the impact of the cascade architecture on both the segmentation and regression stages, as well as the effect of Radial Pair Loss and the overall pose estimation accuracy.

For the cascade architecture, the configuration is as in Sec. 5.2. The parallel architecture takes the same input of \( N = 2^{15} \) points. Its output, however, is \( N \times 4 \), which includes a semantic label and the 3 radii values to each of the corresponding keypoints for all \( N \) points. Segmentation: The first experiment investigates segmentation in isolation. The segmentation output (i.e. \( S \) of Fig. 2a) is compared for both architectures by measuring mIoU against GT. As is the case with the cascade architecture, different loss functions are also applied to the parallel architectures. Initially, the Smooth L1 Loss \( L_s \) is used to train both the segmentation and regression components, as in PVNet [42]. In order to compare with the cascade architecture fairly, the proposed Radial Pair Loss and BCE Loss are then applied afterwards.

The results are shown in Tab. 3. It can be seen that cascade significantly outperforms parallel, by over +15% in testing. Also, the Radial Pair Loss alone boosts performance of the parallel architecture by +13.1%.

Regression: A variation of the above experiment was repeated to evaluate regression in isolation. Here, the regression output (\( M \) of Fig. 2a) is compared for both architectures and loss function combinations, by measuring VCS against GT. The results in Tab. 3 once again confirm that cascade outperforms parallel by +37%, and Radial Pair Loss boosts parallel performance by +9.6%.

It can be seen that cascade significantly outperforms parallel, by over +15% in testing. Radial Pair Loss alone boosts performance of the parallel architecture by +13.1%.
Table 5: Average accuracies of varied 3D descriptors

| 3D Descriptors   | LMO          | YCB          |
|------------------|--------------|--------------|
|                  | ICP          | ADD(S)       | ADD-S AUC | ADD(S) AUC |
| **PointNet++ [45]** | ✓ 73.7       | 96.3         | 95.7      |
|                  | ✓ 74.5       | 96.6         | 96.0      |
| **Point Transformer [70]** | ✓ 73.3       | 95.7         | 95.3      |
|                  | ✓ 73.8       | 96.0         | 95.6      |
| **PPF+knn**      | ✓ 70.8       | 95.5         | 95.0      |
|                  | ✓ 71.7       | 95.8         | 95.2      |
| **FPFH+knn**     | ✓ 70.6       | 94.6         | 93.2      |
|                  | ✓ 71.3       | 94.9         | 93.6      |
| **DGCNN [64]**   | ✓ 70.1       | 92.8         | 90.9      |
|                  | ✓ 70.7       | 93.0         | 91.1      |
| **SubdivNet [25]** | ✓ 65.4       | 92.0         | 90.4      |
|                  | ✓ 66.2       | 92.2         | 90.6      |

Table 6: Impact of Radial Pair Loss $\mathcal{L}_p$ on radii regression

|                      | $\mathcal{L}_r$ | $\mathcal{L}_r = \alpha \mathcal{L}_c + \beta \mathcal{L}_p$ |
|----------------------|-----------------|--------------------------------------------------|
| initial learning rate | $1e^{-3}$       | $1e^{-3}$                                        |
| convergence time     | 5h              | $1e^{-3}$                                        |
| VCS                  | 45%             | 87%                                              |
| ADD(S)               | 47.5            | 68.2                                             |
|                      | $\beta$         | $3h$                                             |
|                      |                 | $90\%$                                          |
|                      |                 | $94\%$                                          |
|                      |                 | 73.2                                             |
|                      |                 | 74.5                                             |

Figure 3: Impact of number of votes on accuracy (VCS and ADD(s)), tested on ape in LMO. The best is 1024 points

**Pose Estimation:** A further experiment evaluated the above combination of elements for the complete 6DoF PE pipeline, the results of which are shown in Tab. 4. The overall ADD(S) is boosted for cascade by +13% on average compared to parallel, with a small runtime sacrifice of 1 fps and a GPU memory cost of 4.7GB.

### 6.2. Comparison of Backend Feature Descriptors

There exist various backend networks in the literature, each encoding a distinct 3D feature descriptor. In order to find the most effective 3D feature descriptor, we compared the performance of RCVPose3D with different backend networks introduced in Sec. 4.2. The result in Tab. 5 show that PointNet++ [45] is the most accurate feature extractor, with Point Transformer [70] as a close second. PointNet was also more efficient, requiring only 1.8M parameters, with the next smallest being Point Transformers with 4.7M. We therefore used PointNet++ in the final RCVPose3D configuration, and for all other ablation experiments.

### 6.3. Impact of Number of Votes

In order to justify the number $M$ of foreground points fed into the regression network, which in turn leads to $M$ votes in the subsequent voting module, we trained the network with different numbers of votes forwarded through regression and into the accumulator space. Here we used the LMO ape object, and varied the number of votes over a range of from $M = 2^7$ to $2^{11}$. The remaining hyperparam-

### 6.4. Impact of Radial Pair Loss $\mathcal{L}_p$

In order to show the impact of the proposed $\mathcal{L}_p$, we trained a radii regression network with the same configuration in Sec. 5.2 but using $\mathcal{L}_r$, and compared it with the combined $\mathcal{L}_r + \mathcal{L}_p$ loss. We then use VCS, the newly proposed score proved to be consistent with ADD(S) in Sec. 3 and Sec. 6.1, to evaluate the regression performance. As shown in Tab. 6, the network supervised by $\mathcal{L}_p$ is not only more accurate, but it also converges faster. Performance actually doubles for learning rate $1e^{-3}$ in which the network does not perform well using $\mathcal{L}_r$.

### 7. Conclusion

We propose a novel cascade architecture for 6 DoF PE from pure point cloud data, i.e. without RGB information. PointNet++ [45] is selected for the segmentation and regression backbones, after carefully considering different 3D feature extractors. A novel radial pair loss function ($\mathcal{L}_p$) is proposed and shown to further improve the performance. Finally, a novel score, Vote Count Score (VCS), for the accuracy of the regression network voting technique (VCS) is proposed and shown to improve training. We achieve competitive results on two popular datasets, LMO and YCB, where RCVPose3D outperforms the SOTA methods that use pure RGB information. When compared to methods that input RGB-D and RGB + point cloud data, RCVPose3D is the best performing method in YCB with the ADD(S) AUC metric. It is also the second best for other combinations of datasets and metrics. Lastly, our time performance is 15 fps, which is competitive with other SOTA methods.

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