Evaluation of dynamic point fields in the case of same class deformation for CAD-models

Martin Drzewiecki
Technische Universität Wien
Vienna, Austria

***Abstract*—Dynamic point fields [1], by Sergey Prokudin, shows a promising mix of explicit and implicit neural reconstruction using point clouds. The transformation obtained by this method give each point a path in which it has to move to reach the destined spot in the final target point cloud. Since this method is point-based, it has a lower computational cost and is faster than other surface reconstruction methods. With this in mind, the task of object recognition of a novel object can be done with a reduced pipeline, since no specific model is required or has to be trained or known.This evaluation will be done for rigid 3D CAD-models of the same class by two simple methods, the Chamfer distance between the predicted/deformed point cloud and the target and a visual color representation of each point corresponding to its original coordinate, with plausible results.**

***Index Terms*—point cloud, deformation, Chamfer distance, as-isometric-as possible**

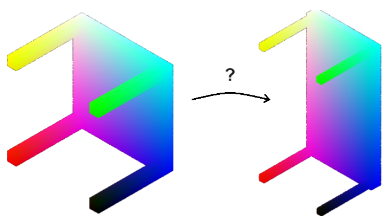

Fig. 1. point cloud deformation of objects from the same class, left the source and right the target model

I. Introduction

For a human, it is a simple task to recognize if an object belongs to a specific class and therefore interact with it as intended. The same task, of object recognition and manipulation, is more challenging for a robot. The object has to be trained or at least known to differentiate and understand its handling. The proposed method of "dynamic point fields" [1], by Sergey Prokudin, is an interesting approach. It is point-based and allows a fast surface reconstruction and deformation of point clouds. Since the main goal was on smooth animation, e.g. interpolation and extrapolation between a source and a target pose of the same model. In this work the deformation will be tested on different, but similar models from the same class. The evaluation will be done in two ways, the Chamfer distance between the deformed and target point cloud and a visual confirmation of the shape and its color coding, which is corresponding to the coordinate of a given point in the original model. The CAD-models used in this project are from the Subset "10-Class Orientation-aligned Subset" which is provided by Princeton (https://modelnet.cs.princeton.edu).

II. Related Work

A. Dynamic point field

The method, by Sergey Prokudin, is the base of this project. It uses point clouds as primitives and compared to other neural rendering methods it provides less computational afford and gives access to point-based approaches. It consists of three main parts, the point-based surface representation, which is essential for CAD-models, which are used here, since these have only a few vertices to work with. The second and third are the point-based non-rigidly deformation of these surfaces and the guided learning regime.

III. Methods

Dynamic points and deformation fields are represented as a sequence of point clouds, which are determined by a transformation given by the neural network. Thought this transformation, each point is following a set path, the sequences, to its target position. The losses used for learning are obtained from the Chamfer distance, a guided correspondence and the as-isometric-as possible constraint.

As-isometric-as possible is a constraint for the deformation and ensures that the distance between a defined set of points is preserved. This guarantees a slower deformation and provides a restriction in case of different object classes, depending on its shape and similarities.

Chamfer distance is the sum of the distances between the points of a source point cloud and the nearest point in the target point cloud. This represents how similar these two sets of points are. It is used for both, the loss for the deformation and evaluation for the deformed and the target point cloud.

Point colors are corresponding to the starting coordinate in the original model. Due to the transformation process, it is difficult to tell where which point started and ended. The coloration will show how plausible the deformation is in regard to its transformation process.

IV. Experiments and Results

The first experiments were done only with Chamfer distance and AIAP Losses, to determine how this method will behave for two different models of the same class. The model was trained both models visible in Fig. 1, the left was the source and the right one was the target. In addition, objects from another class were added to observe the inter class relation of the trained model. As expected, the gap between other classes or not similar object was significant. The results are shown in Fig.2 and in Table I

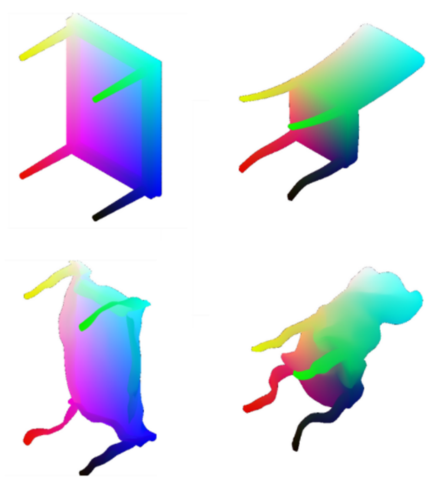

Fig. 2. Point cloud deformation of different point clouds from different classes with no guidance training. Top are the source clouds, bottom the deformed and from left to right table nr. 61, chair nr. 03 and sofa nr. 45. (source and target for the model training are shown in Fig.1)

TABLE I
EVALUATION OF THE CHAMFER DISTANCE FOR DIFFERENT MODELS WITHOUT GUIDANCE

Model	*Loss weight*	*avg. Chamfer distance*
Table Nr.31	Chamfer = 1e3 AIAP = 1e3	0.0142
Table Nr.61	Chamfer = 1e3 AIAP = 1e3	0.0079
Chair Nr.03	Chamfer = 1e3 AIAP = 1e3	0,2160
Sofa Nr.45	Chamfer = 1e3 AIAP = 1e3	0,0940

To get a better result and a point distribution with a smoother color gradient, the guidance loss will be added to the training. In the case of CAD-models, a simple attempt was made to calculate some points which could have a correspondence, but it was not robust and precises enough. For specific models, the correspondence was forced by manually finding a similar point in their structure, e.g. the outside corners of the surface and of each leg. The results show that the chosen key points are correctly positioned, but the surface and legs still ”wobbly” and deformed. Although often the guidance loss increased the total loss which resulted in a much worse and not recognizable shape, which resultes in a higher average chamfer distance. The results are dependent on the set weights for AIAP, Chamfer and Guidance loss and have to be balanced correctly. A weight distribution of AIAP weight=1e3, Chamfer weight=1e3 and Guidance=1e4 seems to be a good middle point between keeping the shape and being correctly deformed, see Fig. 3 and Tab. II.

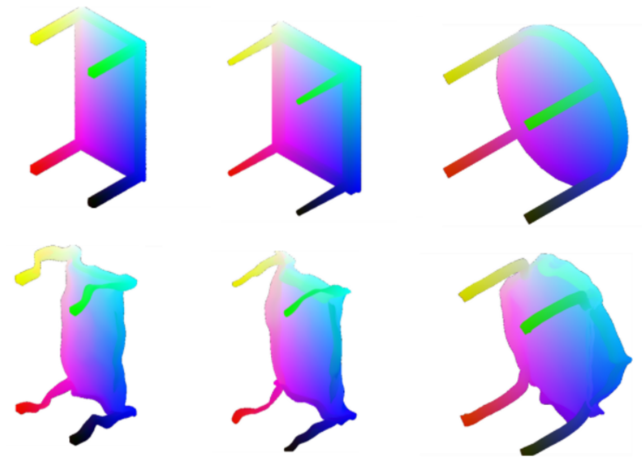

Fig. 3. Point cloud deformation of different point clouds from the same class with AIAP, Chamfer and guidance trained model. Top are the source clouds, bottom the deformed and from left to right table nr.31, table nr.61 and table nr.07. (source and target for the model training are shown in Fig.1)

TABLE II
EVALUATION OF THE CHAMFER DISTANCE FOR SAME MODEL BUT WITH AND WITHOUT MANUALLY SELECTED CORRESPONDENCE POINTS

Model	*Loss weight*	*avg. Chamfer distance*
Table Nr.31	Chamfer = 1e3 AIAP = 1e3 Guidance (manual) = 1e4	0.0236
Table Nr.61	Chamfer = e3 AIAP = 1e3 Guidance (manual) = 1e4	0.0189
Table Nr.07	Chamfer = e3 AIAP = 1e3 Guidance (manual) = 1e4	0.0453

V. Conclusion

The results show, that if the models are very similar, a point-based deformation method like this only allows the recognition of the shape. This is not satisfying enough if object manipulation is desired, since a detailed point cloud could not be obtained. The guidance approach in this work is done manually for specific models and therfore lacks the robustness and versatility. To get clearer results, a more sophisticated method has to be used for creating a correspondence, like ”neural descriptor fields” by Simeonov [2]. There the points receive a descriptor with the information about their distance to a set reference, in the case of the original paper a mug handle and in this case it could be the bottom of a leg or the center of the tabletop. This then could be used as a correspondence for the guided training to obtain model correspondences.

References

[1] S. Prokudin and Q. Ma and M. Raafat and J. Valentin and S. Tang, “Dynamic Point Fields,” arXiv:2304.02626,2023.

[2] A. Simeonov and Y. Du and A. Tagliasacchi and J. B. Tenenbaum and A. Rodriguez and P. Agrawal and V. Sitzmann, Neural Descriptor Fields: SE(3)-Equivariant Object Representations for Manipulation, arXiv:2112.05124, 2021.

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