Algorithm for the Integration/Registration of Three-Dimensional Point Clouds Based on Deep Learning Techniques

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Abstract: In this research work, an algorithm that involves Deep Learning techniques is proposed. With this algorithm is expected to obtain a correct registration of point clouds captured in occlusion environments, high reflectance and missing data.

1. Introduction

With the continuous development of three-dimensional (3D) reconstruction techniques and the increase in the applications in which this technology can have a place, many methodologies have emerged that try to solve the problem of registering and aligning point clouds located in random positions or when they do not have an estimate of the transformation that differentiates them. In this three-dimensional reconstruction process, after scanning or obtaining data from different points of view, one of the main challenges is establishing the corresponding points between the different captures to correctly align that pair of point clouds (integration or registration) based on the same reference system. For that reason, it is necessary to adjust and align point clouds corresponding to scans of the object or scene in question, taken from different points of view. In this process, the main problem is to find the rigid transformation T (specifically find the rotation parameters R and translation t), according with 1,

$$P_f = \mathrm{T}\ \{\ P_d \cdot R + t\ \}, \qquad (1)$$

where P_f is a fixed point-set, P_d is a displaced point-set. These parameters align the corresponding points expressed in a reference coordinate system without affecting the surface morphology or the object to reconstruct [1]. However, distortions, high reflectance of objects and occlusions, as well as noise, missing or inconsistent data make that this problem be challenging

2. Registration and correspondence of points

The Iterative Closest Point (ICP) [2], is perhaps one of the best known methods to carry out this alignment or registration of 3D point clouds. In theory, it works because it is possible to find the rotation between two point clouds by singular value decomposition. The ICP algorithm works for equal point clouds, differentiated only by a rigid transformation, but for point clouds that are disordered, occluded, or have missing data, it does not perform well, due it can converge to a local minimum [2]. Therefore, the main problem of point cloud registration is based on establishing the correspondence of the points for their subsequent alignment.

3. Point cloud comparison

To establish the correspondence of points, in the first instance, a way to compare the point clouds is needed, for this we use Deep Point Cloud Distance (DPDist) [3], which represents the point clouds in the form of a modified fisher vector 3DmFV [4], and calculates a quantitative metric between the two point clouds using a convolutional neural network. Thus, with DPDist the representation of the coordinate system is changed to a two-dimensional matrix, which through statistical values describes the distribution of points in space according to a Gaussian grid (Figure. 1). The 3DmFV uses 20 statistics calculated for each gaussian found from a Gaussian Mixed Model (GMM) [4], to represent the points in terms of their distribution within the Gaussian grid.

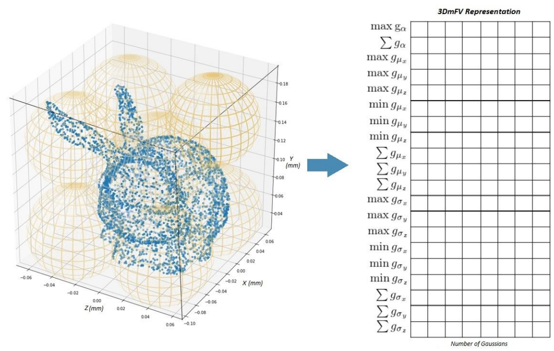

Fig. 1. Representation of a point cloud using the 3D Fisher Vector.

From this representation, it is possible to generate a continuous underlying surface of one of the two point clouds (cloud A), to compare it with the other point cloud (cloud B), which allows the comparison of disordered point clouds, with points missing and mismatched.

The use of a matrix representation allows the neural network to perform training by locations, instead of calculating a representation for all locations [3]. This reduces the complexity of processing entire point clouds, resulting in efficient and pervasive learning across different categories of objects. The trained neural network is able to predict a set of distances, one for each point in the cloud compared to the continuous underlying surface.

4. Registration and Integration

Once the points of the two clouds have been compared using the DPDist metric, a way of matching the points is developed, taking the aforementioned metric as a reference. The set of points with the lowest DPDist comparison values is taken to establish the coincidence of points between the two clouds to be registered, thus partially avoiding the ICP problem when the correspondence of the points is unknown. Once the matching is established, the ICP is executed with the clouds already ordered. Depending on the result, the resulting point clouds are compared with DPDist, the matching of points is established and we execute ICP again, obtaining better results in the comparison as more iterations of the ICP are performed. This iterative process should end at the moment when the two point clouds are integrated and/or registered.

5. Results

It is expected that this algorithm allows the correct integration of two sets of clouds. However, in the development of the investigation two problems are taken into account. The first is the integration or registration of clouds whose structure is symmetrical. It can be fixed by modifying this comparison metric (DPDist) so as not to lose the generality of the point cloud. The second is the stopping criterion for the algorithm. In the case of registering two similar clouds, the optimal metric that meets the criteria must be chosen and allows us to stop the algorithm when the clouds are fully registered. For this, we think of the use of metrics such as the comparison of centroids, Euclidean distance, and even DPDist itself.

References

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