Noise Robustness Analysis of Point Cloud Descriptors

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Abstract. In this paper, we investigate the effect of noise on 3D point cloud descriptors. Various types of point cloud descriptors have been introduced in the recent years due to advances in computing power, which makes processing point cloud data more feasible. Most of these descriptors describe the orientation difference between pairs of 3D points in the object and represent these differences in a histogram. Earlier studies dealt with the performances of different point cloud descriptors; however, no study has ever discussed the effect of noise on the descriptors performances. This paper presents a comparison of performance for nine different local and global descriptors amidst 10 varying levels of Gaussian and impulse noises added to the point cloud data. The study showed that 3D descriptors are more sensitive to Gaussian noise compared to impulse noise. Surface normal based descriptors are sensitive to Gaussian noise but robust to impulse noise. While descriptors which are based on point's accumulation in a spherical grid are more robust to Gaussian noise but sensitive to impulse noise. Among global descriptors, view point features histogram (VFH) descriptor gives good compromise between accuracy, stability and computational complexity against both Gaussian and impulse noises. SHOT (signature of histogram of orientations) descriptor is the best among the local descriptors and it has good performance for both Gaussian and impulse noises.

Keywords: 3D descriptors, features histogram, noise robustness, point cloud library.

1 Introduction

Advances in 3D generation devices are resulting in the popularity of 3D images and many fields have ventured the use of 3D sensors. Computer vision applications such as object recognition, detection and content based retrieval are already established topics for 2D images processing. However, due to the huge amount of information in 3D data, 3D computer vision applications have only been explored in the recent years. This is mostly due to the advances in computing power and storage devices [1]. Furthermore, providing a unique description to the point cloud data is an important step for many 3D applications. 3D description algorithm tends to focus more on the

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structure and the shape of the point cloud unlike the 2D descriptor which only describes the appearance and texture of the points [2].

Different 3D surface detection and description algorithms have been proposed in the literature. 3D keypoints detection methods focus on extracting distinct points on the surface that can be uniquely identified. The point cloud library (PCL) includes many types of 3D descriptors among others point cloud data processing and presentation tools [2]. For recognition and matching applications, surface descriptors provide a very useful and unique signature for a given 3D point cloud. Surface detector and descriptors are always coupled together so that the detectors identify the salient regions (points) within the point cloud while the descriptors assign a unique signature to it. In the recent years, various types of 3D descriptors have been presented to the community, thanks to the availability of required computing power which was not viable in the past [2].

This paper presents a new study for evaluating the robustness of famous surface descriptors in the presence of noise. It is widely known that 3D sensors suffer from noise which is very challenging and hard to remove specially in the depth direction. Despite the studies conducted on the performances of 3D descriptors, no study was presented on evaluating their robustness to various noise conditions. As noise is a common problem in real applications, it was difficult to judge which method will produce the best results. Indeed, previous comparisons have focused on repeatability and accuracy of detected keypoints in the 3D data [2] regardless of the noise or degradation that the image is subjected to. Therefore, the performance results are quite misleading since some good descriptors may fail dramatically in the presence of noise.

Thus, an extensive evaluation of noise robustness of 3D descriptors is presented in this paper. The remaining of the paper is organized as follows: Section 2 briefly presents nine 3D descriptors commonly used in the literature and available in the PCL library. Section 3 explains the evaluation methodology for these descriptors as well as the type of data and noise being used in the studies. Section 4 summarizes the evaluation results and discusses the robustness of the operators to varying level of noise. Finally, Section 5 concludes this paper with main findings about the performances of surface descriptors in the presence of noise and gives recommendations to achieve good performances with the discussed descriptors.

2 Related Works

This section covers previous research on 3D descriptors analysis presented in the literature with focus on the evaluation metrics used in each study. In addition, this section also covers studies about noise modeling for 3D sensors with emphasis on the Kinect sensor because it is commonly used in many vision applications.

2.1 Evaluation of 3D Descriptors

Tombari et al. [3] presented some performance comparison when they introduced SHOT descriptor including noise robustness. However, they only compared SHOT against what was widely available at that time which was spin images (SI), 3D shape context (3DSC) and expectation maximization descriptors. Sukno et al. [4] presented a comparative study of different 3D descriptors for recognizing craniofacial landmarks. The objective of their study was to investigate the accuracy and the usable range of these descriptors on per-landmark bases. They had investigated 26 landmarks using 6 descriptors (SHOT, SI, 3DSC, USC, PFH, and FPFH). They found that the average accuracy among all experiments can give misleading results as it was heavily influenced by the extrema values. For example, they found that 3DSC has the best average accuracy but it is only best for 5 out of 26 landmarks while SHOT and SI provide better results for more than 8 landmarks. Aldoma et al. [2] presented an extensive evaluation of different local and global 3D descriptors available in the PCL library. However their evaluation focused mainly on the implementation of these descriptors in PCL library and they showed a complete implementation pipeline for both local and global descriptors. These descriptors were compared in terms of accuracy and descriptor size without considering the effect of noise.

2.2 3D Sensor Noise Modeling

3D data can suffer from various types of noise depending on the type of sensor used. General laser rangefinders have better accuracy compared to ultrasound as they suffer less attenuation (and scattering) from the transmission medium [5]. Although both sensors show high errors when scanning a reflective or transparent object such as a glass wall [6].This paper focuses on Kinect sensor because it is widely used in robotics and computer vision applications. In addition it is handy, easy to use and comes at low price compared to other type of 3D sensors [7]. Khoshelham and Elberink [8] conducted noise analysis for Kinect sensor and recommended its use for short distances (up to 3m) as the quality of measurement degrades at larger distances due to noise. Cai et al. [9] presented a detailed modeling of Kinect sensor noise and they concluded that the sensor's SNR ratio decreases quadratically with the depth. Similar findings have been reported by Zhang and Zhang [10] in their study for calibrating depth and RGB sensors.

Sun et al. [5] worked on characterizing noise of 3D scanner (Konica Minolta Vivid 910), they concluded that the noise present in this scanner is neither Gaussian nor have independent distribution. In addition, they managed to synthesize the noise in this scanner using Gaussian like distribution based on Fourier spectrum of the 3D data. Camplani and Salagado [11] have shown that noise present in Kinect data have Gaussian distribution and can be considered as white noise. Nguyen et al. [12] modeled the lateral and axial noise distribution of Kinect sensor using Gaussian probability function. They have found that lateral noise increases linearly with distance while the axial noise increases quadratically.

3 Point Cloud Descriptors

This section briefly reviews some of the well-known 3D descriptors used in the computer vision/graphics societies. These descriptors can be categorized into two

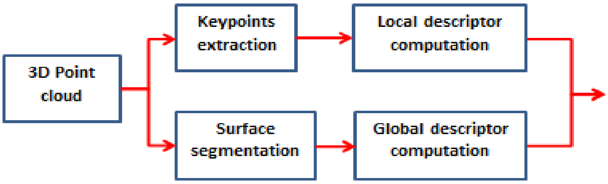


Fig. 1. Global vs. local point cloud descriptors

main groups; global descriptors and local descriptors. Global descriptors describe the global geometry of all points in the point cloud. This is achieved by firstly segmenting the image into coherent regions and then giving a unique descriptor to each segment. On the other hand, local descriptors describe the local neighborhood of selected points in the point cloud known as keypoints.

Fig. 1 illustrates the differences between local and global descriptors [4]. The common aspect among all these descriptors is that they are based on histograms of deviations. Table 1 shows a quick summary about the properties of four global descriptors used in this study.

3.1 Global 3D Descriptors

Global descriptors describe the geometry of subsets of 3D points in the cloud. Global descriptors are more complex than local descriptors and they are used for object recognition and shape retrieval applications. Table 1 summarizes the properties of the following four global point cloud descriptors:

1. Point Feature Histograms (PFH): This descriptor captures the orientation difference between the query point and each of its neighbors [13].
2. Viewpoint Feature Histogram (VFH): This is a modified version of the PFH descriptor that includes the global view direction of the point cloud [2].
3. Clustered View-point Feature Histogram (CVFH): Firstly the object is segmented into smaller regions then computing the VFH descriptor for each segment [14].
4. Ensemble Shape Functions (ESF): It is a collection of 10 shape functions that describe the structure of the point cloud [15].

Table 1. Proproties of Globlal Descriptors

Descriptor	VFH	PFH	CVFH	ESF
Descriptor size	308	125	308/segment	640
Using normal	Yes	Yes	Yes	Yes
Processing time	Moderate	High	Very high	Moderate

3.2 Local 3D Descriptors

Local descriptors describe the local neighborhood around a point in a 3D point cloud. These descriptors are mostly used for surface registration application. Table 2 summarizes the properties of the five local point cloud descriptors that follow:

1. Fast Point Feature Histograms (FPFH): This is a modified version of the PFH by reducing the number of neighbors used for computing orientation differences [2].
2. 3D Shape Context (3DSC): This descriptor considers a sphere superimposed on the query point and divides it into smaller segments. At each segment, the number of points in it is computed and weighted inversely by the segment density [3].
3. Unique Shape Context (USC): USC is a modified version of 3DSC that uses only one unique reference frame for the spherical grid [3].
4. Signature of Histogram of Orientations (SHOT): This is similar to 3DSC but instead of counting the number of points in each segment it computes the relative orientation angle between each point and the query point [2].
5. Spin images (SI): This descriptor encodes the distance between pair of points and the distance between the second point projected on the normal of the query point using a 153 bin histogram [2].
6. Point Feature Histogram (PFH): PFH can be used as local descriptor as well where the search radius is defined to cover the neighborhood of the keypoint only.

Table 2. Proproties of LocalDescriptors

Descriptor	**FPFH**	**SHOT**	**SI**	**3DSC**	**USC**	**PFH**
Descriptor size	33	352	153	125	125	125
Using surface normal	Yes	Yes	Yes	No	No	Yes
Computational complexity	Low	Moderate	Low	Very high	High	High

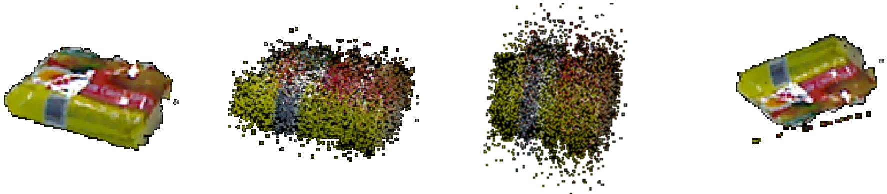
4 Evaluation Methodology

Noise analysis is highly important for selecting good 3D descriptors for noise sensitive applications. This section discusses and justifies the choice of noise type, followed by a discussion on the data collection process and how the experiments have been conducted. Finally, experimental results are presented for both local and global descriptors and an overall evaluation is presented.

4.1 Noise Modeling

3D sensors like any other electronic device can suffer from two types of noise; thermal noise and shot (impulse noise). Shot noise appears as random spikes in the point due to sensor defects and it is much easier to remove with smoothing methods [8]. In the case of Kinect device, shot noise is less dominant and it could be removed within the device itself. Thermal noise is due to electronics carrier and it is characterized by a Gaussian distribution of zero means and suitable standard deviation [11-12]. It is important to note that errors in the Kinect (triangulation based sensor) depend on the distance between the sensor and the object as well as noise. Thus, in order to focus the attention on the Kinect noise, all datasets used in this study are taken from the same distance from the sensor in order to normalize the distance effect.

Fig. 2 shows point cloud data corrupted with Gaussian noise at two different variances and one sample of impulse noise. It is clear that Gaussian noise degrade the point cloud integrity more than the impulse noise because it affects the whole point cloud. Impulse noise appears at random location but with large magnitude (noisy points appear to have extreme depth values).

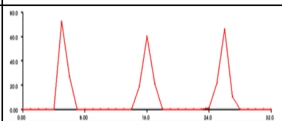
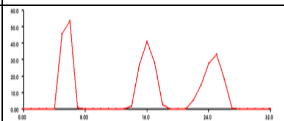
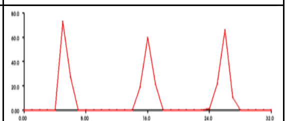
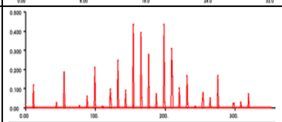
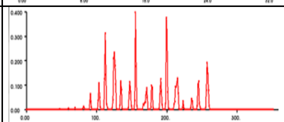
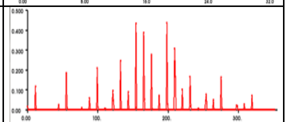
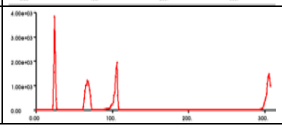
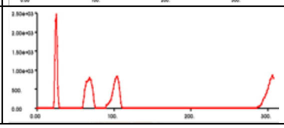
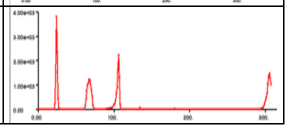


noise free Gaussian noise ($\sigma = 2\%$) Gaussian noise ($\sigma = 8\%$) Impulse noise ($d = 10\%$)

Fig. 2. Samples of point cloud data corrupted with Gaussian and impulse noise

Table 3 illustrates examples of histograms for three descriptors (FPFH, SHOT and VFH) before and after adding the noise to point cloud. Two types of noise have been considered; Gaussian with variance of 10% and impulse noise with density of 10%. Since the Gaussian noise affects the whole image, most descriptors are expected to perform poorly. In contrast impulse noise affects parts of the image only and this makes descriptors more robust to this type of noise and it could be eliminated by a simple smoothing operation. FPFH exhibits significant change with Gaussian noise but remain stable for impulse noise. SHOT descriptor exhibits large change due to Gaussian noise and the locations of the peaks changes while it is stable for the impulse noise. VFH descriptor exhibits small changes due to Gaussian noise and no noticeable change for the impulse noise.

Table 3. Sample for 3D Descriptors with and without Noise

	Without noise	Gaussian noise (1% variance)	Impulse noise (1% density)
FPFH			
SHOT			
VFH			

4.2 Data Collection

For comprehensive evaluation of 3D descriptors in the presence of noise we use two dataset. The first one is public dataset (RGB-D dataset) from the Washington

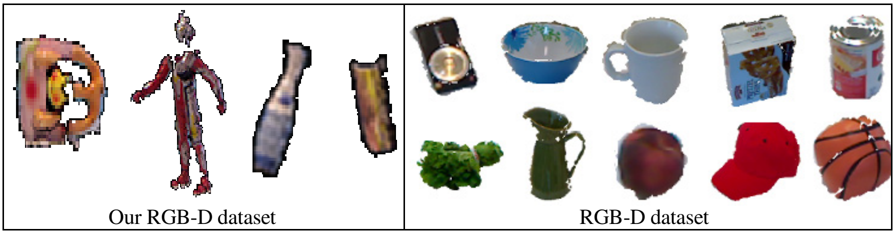


Fig. 3. Sample of Kinect acquired object used in the experiment with object acquired at our laboratory and object from Washington University (RGB-D dataset) available on internet [16]

University [16]. This contains around 300 different objects at variable view angles. All the data have been acquired at a distance of 1m from the sensor. The second dataset has been collected at our laboratory which contains 50 objects scanned using Kinect sensor at a distance of 1m from the sensor as well.

4.3 Evaluating Local Descriptors

The procedure for assessing the local descriptors (SHOT, 3DSC, USC, FPFH, PFH and SI) starts by extracting keypoints from the noise free data. Since local descriptors describe the neighborhood of a point, the same points should be maintained in the query and training dataset. In this experiment, 14000 3D SIFT keypoints have been extracted only for the data without noise and then the descriptor of this point is computed in the training and query datasets. The training descriptor is the descriptor computed for all samples in the dataset before adding noise. In the query stage, 10 levels of Gaussian and impulse noises were added to the point cloud data. For each noise type and level, the local descriptor is computed for each of the previously extracted keypoints. The noise variance or density for Gaussian and impulse noise respectively has been varied from 0% (no noise) to 10%. Each query descriptor is matched against all the training dataset using L1-norm and the matching score is computed using Equation (1). This matching score was introduced because it gives a rating of how far is the best match from the ground truth. The constant epsilon has been added to avoid undefined numbers in the case of perfect match. For fairness to all descriptors, the support size of computing surface normal was fixed at 3cm and the support size for computing the descriptor was fixed at 5cm.

$$F = \frac{bestMatchDistance + \epsilon}{trueMatchDistance + \epsilon} \tag{1}$$

Fig. 4 shows Gaussian noise response graph (average and standard deviation) for six local descriptors computed for RGB-D dataset (300 objects). Based on average matching rate, USC and 3DSC descriptor scored the best performance as they maintained more than 80% matching rate even with the maximum Gaussian noise level and their standard deviation is less than the one recorded for other descriptors.

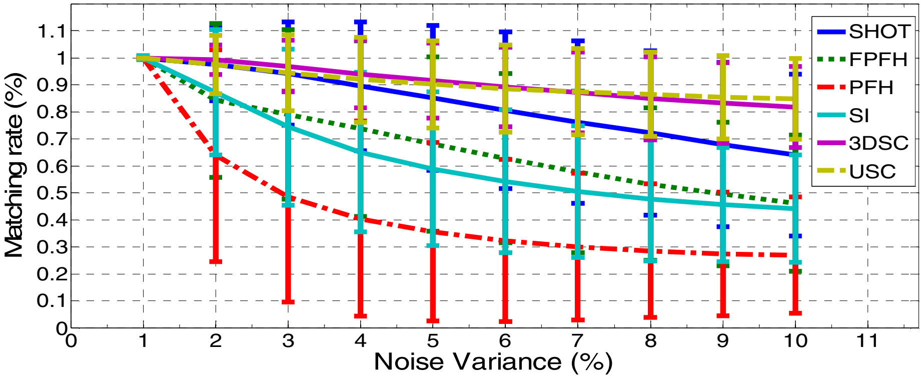


Fig. 4. Performance of local descriptors with Gaussian noise

SHOT descriptor followed next in performance where it scores above 70% matching at the highest noise level. However, it is standard deviation is very large 20%. This is due to the fact that SHOT unlike USC encodes the orientations of the points instead of their numbers in each spherical grid. 3D point orientation is more susceptible to Gaussian noise because it is derived from surface normal. FPFH and SI have poor matching rate as both rely on surface normal for their computations. In addition, both FPFH and SI have very high standard deviation due to noise. This indicates that they are not stable under Gaussian noise effect. PFH descriptor shows very poor performance because it is computed in a local sense as this descriptor is usually used as global descriptor with a larger neighborhood.

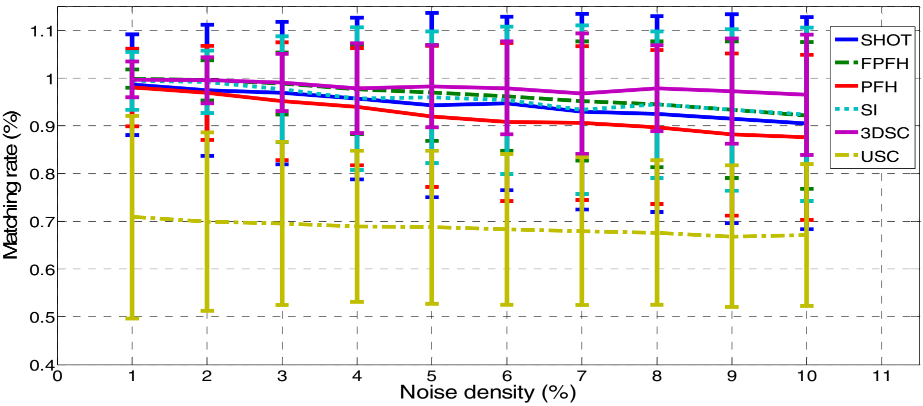


Fig. 5. Performance of local descriptors with impulse noise

Fig. 5 shows local descriptors response to impulse noise. 3DSC descriptor showed excellent performance with 95% matching rate at the maximum noise level however the result's standard deviation increases with noise. This excellent performance could be because 3DSC uses multiple orientations of the principal direction over the spherical grid. USC showed very poor results because it uses only one unique principal direction over the grid. USC scored only 70% accuracy for the minimum noise level and it has standard deviation more than 20%. This indicates USC does not only give poor results with impulse noise but it is also not stable under this noise condition. Normal based descriptors (SI, PFH, FPFH and SHOT) showed good matching rate which is around 90% at the maximum noise level and their standard deviation increase with noise density to up to 20% in the case of SHOT descriptor whereas the standard deviation of other descriptors remain below this value.

4.4 Evaluating Global Descriptors

In global point cloud descriptors, the whole object was treated as one segment for computing the descriptor. Initially, a database of descriptors has been created for all point cloud objects used (training dataset). In the query stage, each of the point cloud objects was corrupted with noise similar to the method for local descriptors. Four global descriptors have been investigated (VFH, PFH, CVFH and ESF). Fig. 6 shows matching rate of global descriptors when Gaussian noise was introduced. The figure displays both the average matching rate for 300 objects (RGB-D dataset) and the standard deviation of the results as a measure for matching stability. Generally, CVFH and VFH have better performance than PFH and ESF. However the results exhibit large variations between different samples. At low noise levels VFH has better matching rate than CVFH but when the noise level is increased CVFH is better. This is because CVFH was computed for small segments while VFH was computed for the whole object thus it includes more noise. PFH descriptor has low performance than VFH and CVFH and at 10% noise variance it goes down to 50% matching rate. In addition, the standard deviation recorded for PFH is much higher the VFH and CVFH. ESF has similar performance as PFH. However ESF reflects fewer changes due to noise compared to PFH. Poor performance of ESF is because this descriptor has much lower accuracy than other global descriptors even without introducing noise [2]. In addition to that the shape functions that build this descriptor are sensitive to noise.

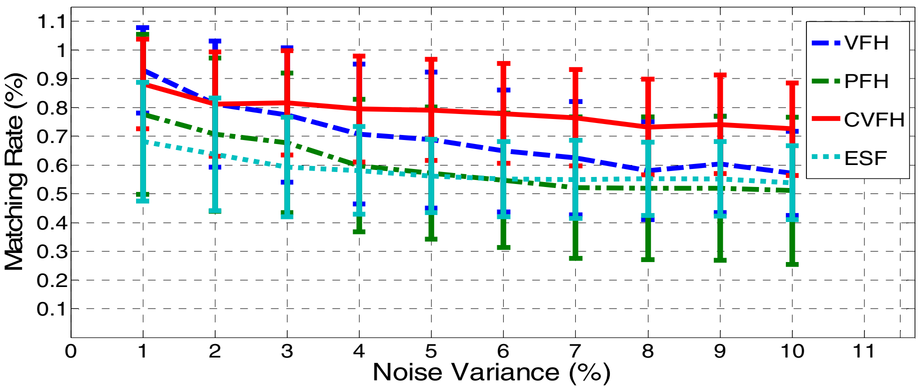


Fig. 6. Performance of global descriptors with Gaussian noise

Fig. 7 shows global descriptors response to impulse noise. Unlike the Gaussian noise normal based descriptors show better response both in average matching rate and the results consistency. PFH leads the global descriptors with overall performance above 90% matching rate even at the maximum noise level and the standard deviation is around 10%. VFH comes next with matching rate above 80% at the maximum noise level and constant standard deviation which is more than 10%. CVFH showed acceptable matching rate for impulse noise which goes down to 70% at the maximum noise level and the standard deviation is slightly increasing with noise. VFH and CVFH have opposite response to both Gaussian and impulse noises because the effect of Gaussian noise is much larger on VFH than CVFH whereas for impulse noise VFH performs better than CVFH. Gaussian noise affects the normal estimation step of both descriptors and since VFH is computed for the whole object it is degraded more than CVFH. Whereas the impulse noise affects the segmentation step of the CVFH descriptor which results different segments at different noise levels which reduces the matching rate. ESF showed poor behavior when impulse noise was introduced with almost a constant matching rate of about 70% for all noise levels and the results standard deviation is below 10% for all levels. This is because ESF does not use normal in it computations and thus impulse ripples are not smoothed and they directly affect the shape functions that build this descriptor.

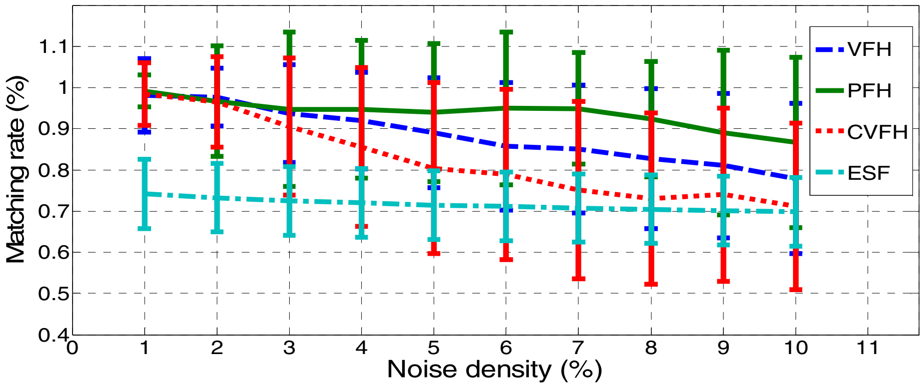


Fig. 7. Performance of global descriptors with impulse noise

4.5 Results Analysis

All the results shown were conducted for the RGB-D dataset because it is larger in size (300 objects). Nevertheless, these results are same as the one obtained from our local dataset (50 objects) except that for our local dataset a background removal step is applied on the point cloud data before computing the descriptors. The previous set of experiments proved that 3D descriptors (both local and global) have very different responses for Gaussian and impulse noises. In general, most of 3D descriptors are more robust to impulse noise than Gaussian noise. This is because impulse noise affects only parts of the object while the Gaussian noise affects the whole object. Although the noise levels tested are very high, some descriptors showed good matching accuracy and consistent behavior for the tested objects.

Descriptors who are based on surface normal (PFH, FPFH, VFH, CVFH, SI and SHOT) are highly affected by Gaussian noise because the surface changes due to noise and the normal component for each point will change as well which lead to a different descriptor been computed. On the other hand the same types of descriptors are very robust to impulse noise because the normal computation step smooth the impulse noise ripples from the surface. 3D descriptors which are based on points count in a spherical grid around the query point (3DSC, USC and to some extent SHOT) are more robust to Gaussian noise. This is because the Gaussian noise is additive and normally with lower magnitude than the point itself. Thus the point will not move from its spherical grid and it will contribute to the same bin in the descriptor despite the noise. While in the case of impulse noise the magnitude of change due to noise is high and the point will be moved from its spherical grid. As a result, the descriptor changes and it produces poor matching results. SHOT descriptor showed a mixed behavior between normal based descriptors and points count based descriptors because it divides the point cloud in spherical grids but instead of encoding the number of points it encodes their orientation differences similar to normal based descriptors. 3DSC descriptor showed excellent results for both impulse and Gaussian noises because it computes the same descriptor for multiple reference orientations which creates multiple descriptors for the same keypoint at different rotations and translations from the query point. This makes the descriptor always able to find the best match. However this comes at a huge computational burden.

5 Conclusion

This paper evaluated the robustness of point cloud descriptors for Gaussian and impulse noises. The study measured the average matching rate and the results standard deviation for six local descriptors and four global descriptors at various noise levels. Both local and global descriptors behave differently to Gaussian and impulse noises. For Gaussian noise, normal based descriptors have reduced performance. This is because the Gaussian noise affects the normal of the 3D points which leads to a different descriptor being computed and thus low matching rate. The same descriptors are very robust to impulse noise because the normal computation step removes impulse ripples from the point cloud. 3DSC descriptor showed excellent robustness for both impulse and Gaussian noises because it creates multiple copies of the same descriptor at different orientations and translations. USC descriptor is similar to 3DSC but rather computed for one orientation showed good matching rate for Gaussian noise. However, it has very poor results for impulse noise. ESF descriptor has poor performance for both Gaussian and impulse noises. In term of results stability most descriptors showed small increase in standard deviation with noise. PFH and SI are not stable with Gaussian noise while USC is not stable with impulse noise.

As a conclusion, 3DSC descriptor showed the best performance among the local descriptors but it has very high computational complexity. SHOT descriptor has good matching rate for both Gaussian and impulse noises and it has moderate computational complexity. Among the global descriptors, VFH descriptor showed acceptable performance for both Gaussian and impulse noises and it has moderate computational complexity compared to PFH and CVFH.

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