

# New approach for 3D object forms detection using a new algorithm of SUSAN descriptor (ID:84)

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**Abstract:** *This paper occurs in the context of object recognition, and in particular, in the detection of 3D objects and their free forms by local descriptors of interest points to identify them. However, it remains to solve a several problems in this area that is related to the large amount of information and invariant to scale and angle of view. In this context, our purpose is to make the recognition of a 3D object from the detection of their interest points and extract characteristics of the detection of each object to facilitate his research in a database.*

*For this reason, we will propose a new robust detector of noise that includes criteria for extracting interest points of 3D objects by specifying their free forms. This detector is based on SUSAN detector using differential measures for compare it with others.*

**Keywords:** *recognition, detection, 3D objects, detector, descriptor, interest points*

## 1. Introduction and preliminary

Today, the computer vision methods are used in many applications such as video surveillance, conduct or 3D reconstruction. These applications typically rely on forms of recognition or monitoring processes. To do this, we need to analyze the images and extract the following features (edges, intensity or functions of morphological models). The most common methods are based on the use of interest points that characterize a corner in an image or object either 2D or 3D. For mapping a set of points of an image to another, a local description is used to extract the information of the neighborhood of each point (pixel values, the light of intensities, gradients). [4]

This description and extraction of interest points has had a long tradition in processing and image analysis.

In the 2D area, the extraction of indices in an image is an essential step in computer vision, that is why the detection of interest points directly from the signal seems the most powerful technique. Furthermore, the detection of interest points is reliable whatever the processed images because they give comparable results on highly textured images like images containing fewer textures. The selection of interest points is done first, because many studies have shown their usefulness [Schmid, 1996], [Gouet, 2000], [9] ... etc. Furthermore, because they have strong local presence in image transformations such as shading, rotation, and the change of viewpoint... etc. [2]

In the field of processing of the 3D model, the detection of interest points is essential for many applications, such as registration, simplify meshes, mesh segmentation, selection of viewpoint and corresponding object recovery. The use of interest points to match 3D shapes has the advantage of local characteristics that are semantically meaningful and also invariant to rotation, scaling, noise, distortion, and joint.[3]

These interest points that are used in the 3D recognition domain are also called "feature points or key points», these points are distinguished in their locality, present and stable at all instances of an object.

In this work, we are particularly concerned with the analysis of the interest points on the 3D objects, and we will make an analysis of interest points based on automatic detection 2D and 3D algorithms.

For this purpose, several combinations of detectors and descriptors of 2D and 3D interest points are experienced on the basis of 3D objects with different properties. The results indicate that the specific method to extract and describe the interest points in the 3D data must be carefully chosen because in many cases the accuracy suffers from an excessive reduction of the available points.

As we said, our article is included in the field of recognition of 3D objects, especially in search of a new detector of the interest points that are going to do the extraction and detection of free forms of 3D objects in

images to facilitate their recognition and search in a database.

## 2. Related Works

This article considers interest points and the different types of 2D and 3D descriptors, which is why we will look on these detectors and see the famous methods of different detectors of interest points dedicated to images and 3D objects.

### 2.1 2D Detectors

- **Harris**

(a) **Detector based on Harris matrix:**

Harris and Stephens (Harris, et al., 1988) set this detector, which is based on the calculation of the autocorrelation function, Harris and Stephens brought back to the study of the eigenvalues of Harris matrix (second order moment's matrix). Knowing that the eigenvalues of this Harris matrix represent principal curvatures of the autocorrelation function, we have three possible cases:

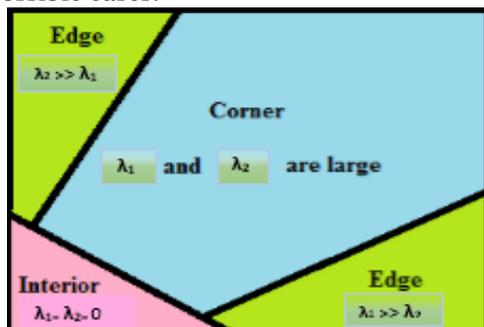


Figure 1. Region types of distributions based on the two largest eigenvalues of Harris matrix (Harris et al., 1988). [7]

- (a) Homogeneous region, if both values are low.
- (b) A contour (transition) if one of the eigenvalues is very large compared to the other.
- (c) A corner (point of interest), if both values are high.

This operator keeps only the structures in the corners, i.e. sufficiently large curvature. Despite their high repeatability, these detectors are sensitive to noise and scaling. Dufournaud et al [14] proposed a multi-scale version of the Harris operator in which interest points correspond to local maxima of Harris detector applied at multiple scales. [1][7]

(b) **Detector based on Harris-Laplacian matrix:**

The Harris-Laplace detector (Mikolajczak, et al., 2004) detects interest points using the Harris function appropriate to the scale. Thereafter, the maximum points of the Gaussian Laplacian are selected to feature scale. The Laplacian is the trace of the matrix of Harris. These detectors are invariant to scale and affine transformations.

- **Lowe SIFT**

The SIFT detector (scale-invariant feature transform) is presented in [Lowe 99], his goal was to locate key points with a vector descriptor in order to characterize an object and be able to recognize it by comparing the characteristics of the points with the elements of a database. Another objective is also to solve the problem of scaling that usually presents problems to other detectors. [5][8]

- **Kadir**

Kadir and Brady introduce the salient region detector, which is based on the probability density function (PDF) of the intensity values that is estimated by the values of the histogram of gray levels in a circular patch on a scale and an accurate position. This detector is invariant to scaling and rotation. [1]

- **Moravec**

The oldest work concerning the iconic detection of interest points is those of Moravec [11]. The principle was to calculate the variations of luminous intensity in four directions parallel with the lines and the columns of the image and then measuring the differences between a rectangular window around a pixel and four neighboring windows. A point having intensity variations in all directions is an interest point. [2]

- **SUSAN Smith**

This detector is proposed [Smith 97] by Smith et al, is as follows: In a circular neighborhood around the pixel of interest called (nucleus), we construct the USAN mask (Univalue Segment Assimilating Nucleus) where we only keep pixels with the same intensity as the nucleus (see figure below) and determining interest points as follows:

- If within this disc, all the pixels have the same intensity as the nucleus, then it is in a homogeneous zone.
- If in this disc, half of the pixels have the same intensity as the nucleus then the original pixel is on a contour.
- If only a few pixels in this disc have the same intensity as the nucleus, then one is in the presence of a corner. [5] [2]

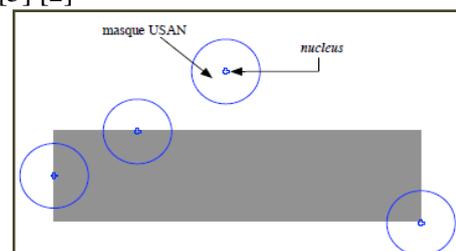


Figure 2. SUSAN Detector - Illustration of the principle of SUSAN detector, the number of USAN mask pixels with the same intensity

as the center to determine whether the studied pixel is in a homogeneous zone on an outline or whether it is a corner.

This approach has the advantage of being fast but its major drawback is the poor location of interest points.

- **SURF**

SURF (speeded up robust features) is a robust image descriptor, presented by Herbert Bay et al. in 2006, and which can be used for object recognition or 3D reconstruction. It is partly inspired by SIFT and the standard version is much faster than SIFT, then, the authors ensure that it is more robust to different image transformations than other descriptors.[1]

## 2.2 3D Detectors

- **Harris 3D**

(Sipiran, et al., 2010) this algorithm proposes an extension of the method of Harris corners of detection for 3D meshes. It is based on two ways to select the interest points that are available: either, by taking a fixed number of vertices having the biggest answers ,or by a combination of approaches (clustering) to have well distributed interest points. [1][7]

- **3D-SURF**

Another detector of the prior art by an extension of a known method in the 2D is introduced by 3D SURF (Knopp, et al., 2010). This detector defines a 3D Hessian for spatio-temporal primitives. [1]

- **Quality factor**

This detector is based on a quality measure of the interest point introduced by (Mian, et al., 2009) who used to classify detected interest points. [1]

- **Mesh saliency**

Mesh saliency is based on the local curvature of the surface to facilitate the detection of interest points based on the vertices of the mesh to define a local maxima selected as an interest point. [3]

- **Weighted Salient points**

Tangelder and Velkamp (Tangelder, et al., 2003) propose a local approach based on representations by weighted salient points for the consideration of the relative spatial position of the polyhedron object. They applied a PCA (Principal Component Analysis) to normalize the position of the object and then decomposed into a 3D grid for the detection operation and weighting of interest points.[1]

- **3D-SIFT**

Scovanner et al. (Scovanner, et al., 2007) introduce a descriptor SIFT 3D videos with time as a third dimension. For application to human action

recognition in a video sequence, sampling of the training videos is carried out either at spatio-temporal interest points or at randomly determined locations, times and scales. [1][16]

- **Scale-dependent corners (SD-corners)**

[Novatnack ET Nishino][15] Also built a scale-space representation of the model; however, they analyzed the scales independent of each other to detect scale-dependent corners. We will refer to their method as "SD-corners" method.

The authors compute the Gram Matrix of first order partial derivatives of the normal map at each point. If the maximum eigenvalue of the Gram Matrix high at a point then the point is considered to have a high corner response. [3]

- **Heat Kernel Signature (HKS)**

Sun et al (Sun, et al., 2009) use as quality measure the heat kernel calculated on the mesh, the resolution of the heat equation on the space and time permit to build a space equivalent to ladder. Then, the maxima of the core are chosen as interest points. [1]

- **Ground truth (2012)**

In this method, we present an evaluation strategy based on truth soil generated by man to measure the performance of interest point's detection techniques in 3D. Helin Dutagaci, Pan Chun Cheung and Afzal Godil have provided the quantitative evaluation measures concerning the automatic detection of interest points to labeled human points, which were collected through a web-based application. They used a method based on the vote to build the metro truth for 3D models and proposed three measures to assess and to compare algorithms of detection of interest points. [3]

## 3. The 2D/3D and 3D model used

The 3D models used in the algorithm test contains 40 triangular meshes. Some models are standards that are widely used in research of 3D shapes as Human Hand, Smooth, Armadillo, the head of David Teapot, Horse,... These are some objects of the Benchmark database. However, for 2D / 3D models that we tested in our experiments, we created them from the "Sweet Home 3D" software, and which are exploited in our work, contains a set of 3D data that they can be downloaded from our reference site. [On line]

## 4. Interest Points

Comprehensive descriptions prove inadequate when it comes to search for an object in a query image in an

image-based search or just part of the query image. Therefore, the use of local descriptions is a key step in the search for an object in the image databases. To complete this description, it must extract the interest points in discovering areas that present significant information content. Moravec [11] introduced the concept of interest points for the first time as a two-dimensional signal change, such as corners, T-junctions, Y, L...etc

The interest points are usually a discontinuity of gray levels as shown in the figure below, they may also appear at a modification of the structure, object deformation's, stiffness, texture or the geometry of the image.

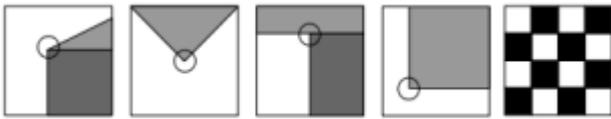


Figure 3. Different types of interest points: single corner, junction 'V' junction 'T' junction 'L' junction 'checkerboard'

#### 4.1 Detection of corners

Detection of corners plays an important role in computer vision, as well as in the 3D reconstruction of the scene. That is why the effectiveness of interest points that has been proven to object recognition in both areas 2D and 3D. Using wedges, we can determine the most characteristic points of an object, reconstruct it, and recognize it.

For that, we will introduce in this article a new corner detection algorithm that is based on SUSAN algorithm.

### 5. The choice of the new approach of SUSAN detector

The 3D local approaches using interest points for detection are based on 2D techniques to define a 3D detector to facilitate the recognition of objects.

The interest point is a special case of interest regions and it is a local inheriting represents an interesting property and essentially to overcome the occlusion of the image. This latter contains several items with more important features than others, and it was the idea of Moravec [11] to use the autocorrelation function to determine the best position of the projection point to any position adjacent contains less information.

The essential problem in the detection is to find robust and automatically enough points for matching and allowing a free form of an object in order to easily identify interest points. To do this, the repeatability of the points taken in several conditions must be met.

Therefore, in this paper, we will introduce a new detector approach to detect the free form of 3D objects in 2D or 3D view based on the 2D SUSAN algorithm.

### 6. Assessment of the new method

This approach does not use the derivatives of the image intensities but it measures in a 2D window the number of pixels having an intensity close to the central pixel of the 3D object and see a large change in intensity signifies the existence of interest point.

This detector allows visualizing the corners and edges of 3D objects by a local object detection through the application of a new circular mask like the circular mask SUSAN.

However, the difference between these two masks, that there is here a subtraction of an element 1 of each pixel of the detected elements, in order that, the interest points detects only all the objects found in the ground.

Then we will make a comparison of all pixels within the mask with the NDG, the nucleus using the comparison equation C used in the basic algorithm SUSAN.

$$C(r, r_0) = e^{-\left[\frac{|I(\vec{r}) - I(r_0)|}{t}\right]^6} \quad (1)$$

Where  $r_0$  the position of the core in the two-dimensional image and  $r$  is the position of any other pixel inside the mask.  $I(r)$  is the luminance of any pixel,  $t$  is the threshold variation of luminance and  $C$  is the result of the comparison, which is made for each

pixel inside the mask. Then we compute the number of pixels  $n$  in the new mask having the same NDG as the nucleus by the total of the comparison results:

$$n(\vec{r}_0) = \sum_r c(\vec{r}, \vec{r}_0) \quad (2)$$

More precisely, we define the new area USAN of these objects tested by a subtraction of its size with a selected geometric threshold, which corresponds to the minimum contrast determination contours.

Finally, we finish the operation of detection by the removal of false positive responses using the USAN center of gravity, and then we remove the non-maximums to find interest points that detects the free form of 3D objects tested.

The new descriptor is not interested in the shape of the structure of the local image around a point located as it reflects detect 3D objects. On the opposite, it analyzes several regions separately using direct local measurements by determining the borders of individual regions with strong curvatures.

## 7. The Robustness of the new detector against the noise

Interest points have characteristics that distinguish them from other areas of the image or object, such as a strong contrast.

Historically, the authors sought to extract the objects corners in an image, the detectors did not find just the corners, but also other points in the textured areas or in the presence of noise [5].

By applying the mask generator and despite the noise detected Gaussian or salt and pepper on objects, the approach has detected 3D objects in 2D view, but despite the robustness of SUSAN algorithm against noise, it detects the interest point but with several points of the noise in the image or object.

Usually, this detector does not require derivatives in the presence of noise, then, the performance is good

### (a) 3D objects of the database Benchmark

Table 1. The difference between the detection of 3D objects by SUSAN detector (DS) and the new SUSAN detector (NDS) "Benchmark"

3D Object	SUSAN Detector	The new Detector SUSAN (NDS)	
	Radius=2 ; alpha=50 ; r =2	Radius=2 ; alpha=50 ; r =2	Radius =20 ; alpha=50 ; r =2
			
<b>Camel.off</b>	Interest points number = 5120 Elapsed time is 2.41 seconds.	Interest points number = 779 Elapsed time is 1.46 seconds.	Interest points number = 2487 Elapsed time is 2.29 seconds.
			
<b>Horse.off</b>	Interest points number =2622 Elapsed time is 1.30 seconds.	Interest points number = 386 Elapsed time is 1.20 seconds.	Interest points number =1110 Elapsed time is 1.28 seconds.
			
<b>Homer.off</b>	Interest points number =5928 Elapsed time is 2.56 seconds.	Interest points number = 685 Elapsed time is 2.46 seconds.	Interest points number = 2393 Elapsed time is 2.50 seconds.
			
<b>Bimba.off</b>	Interest points number = 9828 Elapsed time is 3.95 seconds.	Interest points number = 954 Elapsed time is 2.64 seconds.	Interest points number = 2388 Elapsed time is 2.18 seconds.

We resume the results above in the following figure:

and the integrating effect and the nonlinear answers of the principle of Susan allow a high noise rejection.

## 8. Experimental design, materials and methods

As we mentioned in the last two paragraphs, we collected data via our application and applied the old and the new detector of SUSAN algorithm as we described before.

We have performed the analysis on two sets of data, 3D objects of database benchmark and a small database objects created with the software "Sweet Home 3D".

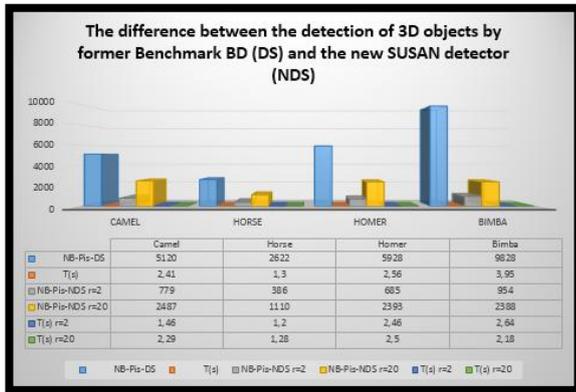
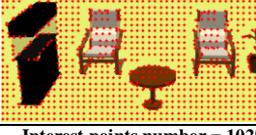
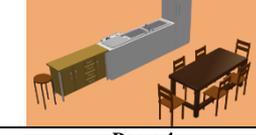
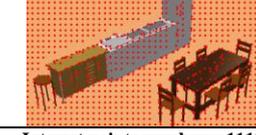
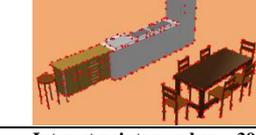


Figure 4. The difference between the detection of 3D objects by SUSAN detector (DS) and the new SUSAN detector (NDS) "Benchmark" After the new mask used, we treated three cases:

- The case of SUSAN detector → there are a total detection of interest points on space and on the 3D object.
- The case of the new SUSAN detector → we saw two cases:
  - If the radius of the mask = 2 → there is a detection of interest points around 3D objects tested to refine the detection of their free forms.
  - If the radius of the mask = 20 → there is a detection of interest points in the space behind the object tested which gives us an appearance and extraction isolated of the 3D objects. detected.

(b) 3D Objects of the software « Sweet Home 3D »

Table 2. The difference between the detection of 3D objects by SUSAN detector (DS) and the new SUSAN detector (NDS) "Sweet Home 3D"

3D Object	SUSAN Detector (DS)	The new Detector SUSAN (NDS)
	Radius=2 ; alpha=80 ; r=5	Radius =2 ; alpha=80 ; r=5
 Room 1	 Interest points number = 1691 Elapsed time is 4.18 seconds.	 Interest points number = 680 Elapsed time is 3.35 seconds.
 Room 2	 Interest points number = 1428 Elapsed time is 3.63 seconds.	 Interest points number = 426 Elapsed time is 2.83 seconds.
 Room 3	 Interest points number = 1029 Elapsed time is 2.92 seconds.	 Interest points number = 347 Elapsed time is 2.43 seconds.
 Room 4	 Interest points number = 1118 Elapsed time is 4.82 seconds.	 Interest points number = 393 Elapsed time is 4.51 seconds.

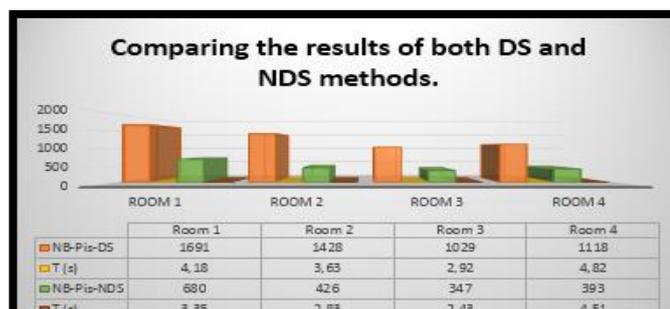
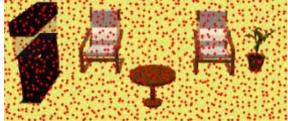
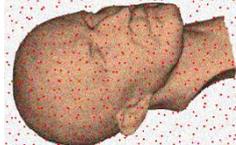
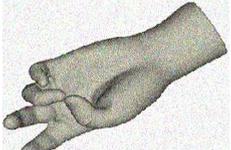
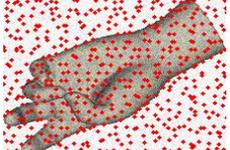
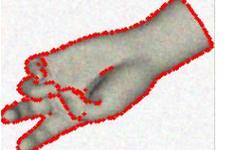
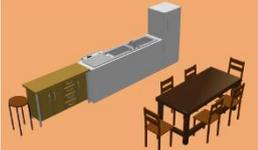
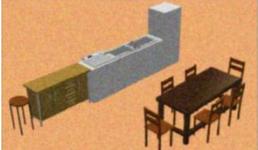
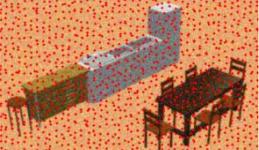
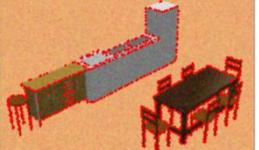


Figure 5. The difference between the detection of 3D objects by SUSAN detector (DS) and the new SUSAN detector (NDS) "Sweet Home 3D"

- Here we have two cases: The first is the SUSAN detector that detects 3D object and its space and the second algorithm that shows the extraction of the free form of tested 3D objects.
- By the New SUSAN detector, we always get less interest points quickly. These points detect the free form of the 3D objects and they are located well on them, against an interest point of another descriptor.

(c) Noisy 3D objects in 2D view

Table 3. The difference between the detection of 3D noisy objects by SUSAN detector (DS) and the new SUSAN detector (NDS).

Room 1	Noisy Room	SUSAN Detector (DS)	The new SUSAN Detector (NDS)
			
		Interest points number = 1078 Elapsed time is 3.20 seconds. SUSAN Detector (DS)	Interest points number = 906 Elapsed time is 3.13 seconds. The new SUSAN Detector (NDS)
3D Object : Maxplanck.off	Noisy Maxplanck		
			
		Interest points number =468 Elapsed time is 1.15 seconds. SUSAN Detector (DS)	Interest points number = 288 Elapsed time is 1.10 seconds. The new SUSAN Detector (NDS)
3D Object : Hand.off	Noisy Hand		
			
		Interest points number = 525 Elapsed time is 3.16 seconds. SUSAN Detector (DS)	Interest points number = 324 Elapsed time is 1.60 seconds. The new SUSAN Detector (NDS)
Room 2	Noisy Room 2		
			
		Interest points number = 1092 Elapsed time is 2.18 seconds. SUSAN Detector (DS)	Interest points number = 917 Elapsed time is 1.73 seconds. The new SUSAN Detector (NDS)

- Here we have two cases: The first is the SUSAN detector that detects 3D object and its space and the second algorithm that shows the extraction of the free form of 3D objectstested.
- By the New SUSAN detector, we get less interest points quickly. These points detect the free form of 3D objects and they are located well on them against an interest point of another descriptor, which is

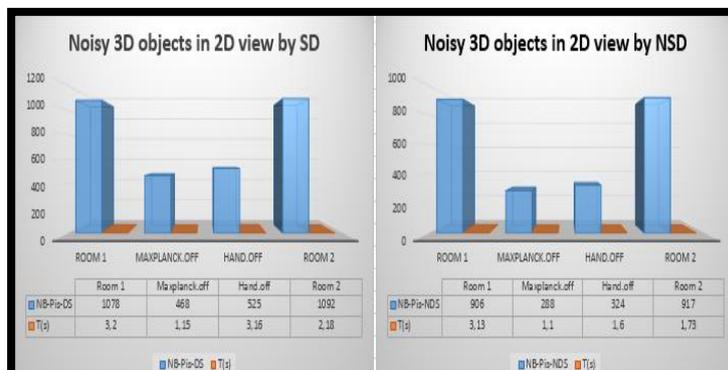


Figure 6. The difference between the detection of noisy 3D objects by (DS) and the new SUSAN detector (NDS)

- Here we add the noise to 3D objects, then we test them by the two SUSAN detectors then we get two types of results:
- For SUSAN detector: we get a random spread of several interest points and no 3D object detection, which always takes a long execution time compared to the new detector.
- For the new SUSAN detector: we get less interest points in a short time compared to the first detector. More than that, the detection of the free form of 3D objects is good and all interest points are well localized. This shows us the true strength of the new detector against noise.

→ In objects recognition, an accurate selection of interest points minimizes the execution time, avoids ambiguity in the calculation of the descriptors, the mapping and sees the true strength and robustness against noise detectors.

## 9. Comparison and Discussion

According to a comparative study of the results obtained in the three tables below, we see that the object detection by the new SUSAN detector is faster compared to the old detector, where we put the same core radius exchange, and delivery always gives quick results relative to the other.

And it's the same for noisy objects in the last table of results, a perfect and clear detection is seen on the new SUSAN detector relative to the old detector, this shows us such efficiency of the new detector for either noisy or no-noisy objects that require considerable computation time. In addition, we see a detection of several interest points by SUSAN detector that are scattered everywhere without specifying the free form of the object, which will value this new descriptor.

In the fact, some features that facilitate the extraction and detection of free forms of 3D objects in 2D images are included in the results, after which facilitates the recognition of these objects studied. In the above results, we calculated the complexity in execution time of each algorithm, and carefully study their effectiveness by comparing two SUSAN descriptors.

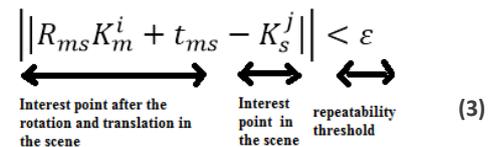
The study of complexity leads to a classification of problems related to the performance of the best known algorithms. A priori, we cannot always measure the computation time on all possible inputs of an algorithm, which leads us to calculate the time complexity of the descriptors and knowing how they are noisy or not. After calculating the complexity of our new descriptor, we found a quadratic complexity  $O(n^2)$  which is smaller than a cubic complexity  $O(n^3)$  which is applied by the old descriptor SUSAN and which show that our detector is faster to be successful than the other comparable descriptor.

## 10. Repeatability

The detected points must be invariant deformation, changes of scale and angles and robust to the noise. This means that, the detection is to extract the same point after deformation or adding noise to the original model.

In (Schmid et al., 2000), the evaluation of the performance of interest point detectors is made by measuring absolute repeatability, that is the proportion of interest points whose position is the same passing with a view to another for the same object. An interest point is said repeatable if:

$$\left\| R_{ms} K_m^i + t_{ms} - K_s^j \right\| < \varepsilon \quad (3)$$



Therefore, to measure the repeatability of interest points between the different views / scales, we consider two views: View one (1) and View two (2) of the same object. The actual transformation T (rotation or scaling) is known between the two views, then, we calculate the distance between the positions of each interest point detected in the view 1 and underwent the transformation T and the nearest interest point detected in the view 2. [1]

## 11. Conclusion

The characteristics that we used to a 3D model object in a free form, -interest points- are still present in several objects used in our life.

In addition, the use of global and local descriptors at the same time, and the hierarchical approach that tries first recognition of the full model before only recognizes small sub-models, make it possible to detect in a scene, an object even if it is partially hidden (occlusions).

The algorithm that we developed to facilitate the recognition of a 3D object was to operate both the geometric characteristics to achieve a more robust and stable recognition system.

According to the results achieved on noise, this new approach gives a good performance results that are relatively satisfactory in comparison with those obtained by other algorithms. Moreover, this method can be applied in various image-processing contexts in the computer vision, the edge detection, and in the image segmentation and 3D objects with 2D view.

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