

Fast 3D keypoints detector and descriptor for view-based objects recognition

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Overview



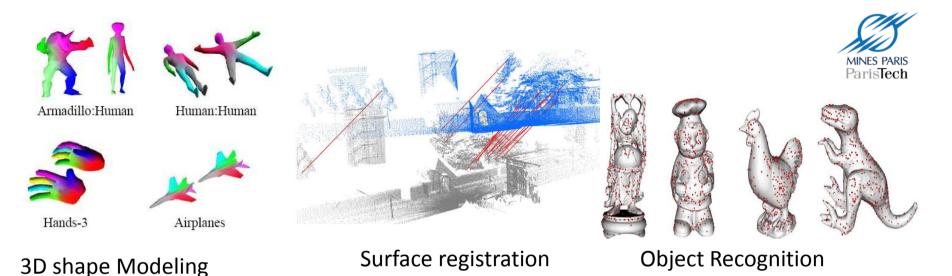
1. Introduction

2. Keypoint Detection

3. Keypoint Description

4. Keypoint Matching

5. Conclusion



 Technological advances have made possible the production of reliable and accurate 3D data

- For a 3D capture of an object: Physical shape + robustness
 - For a 3D capture of an object: Physical shape + robustness -> Growing interest for 3D data
- Processing 3D data presents some issues:
 - Big amount of data
 - Capture conditions (sensor or scene)
- Need compact, invariant and robust representation -> Assures effectiveness for tasks:

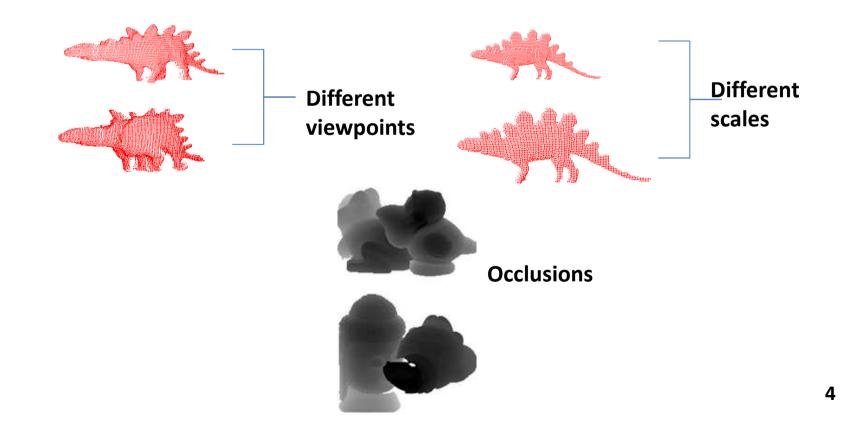


How to characterize the 3D shape for 3D object recognition



Problems related to the real world and sensors:

Invariance to scale, sampling and geometric transformationsRobustness to noise and occlusions





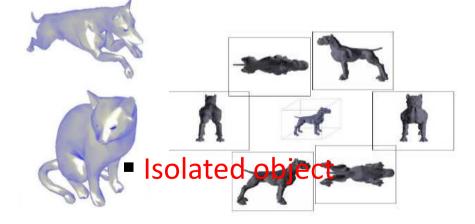
Different input data **formats** in recognition task :

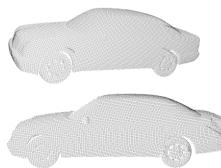
- Point cloud
- 3D Mesh
- Range image (2.5D)

- Partial views
- Whole 3D object

Situated in a whole scene (need segmentation)







Keypoint detection



- Salient point
 - Repeatable and robust
 - Well localized
 - Fast detection
 - Existing:
 - 3D Surf detector [Jan et al., 10]
 - 3D Harris detector [Ivan et al., 10]
 - Gaussian filters [Castellani et al.,08]

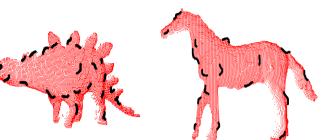
Largest shape variation: How much do the dominant directions of the surface change locally?

- Differential geometry: curvatures and surface normals.
 - Curvature based detectors

Knopp, Jan and Prasad, Mukta and Willems, Geert and Timofte, Radu and Van Gool, Luc, "Hough transform and 3D SURF for robust three dimensional classification", 589–602, ECCV'10.

SIPIRAN I., BUSTOS B.: A robust 3D interest points detector based on Harris operator. In Proc. Eurographics Workshop on 3D Object Retrieval (2010), Eurographics Association, pp. 7–14.

U. Castellani, M. Cristani, S. Fantoni and V. Murino, « Sparse points matching by combining 3D mesh saliency with statistical descriptors"; EUROGRAPHICS 2008; Vo I u m e 2 7(2008), Number 2.







$$SI_{p} = \frac{1}{2} - \frac{1}{\pi} arctg \left(\frac{k_{p}^{1} + k_{p}^{2}}{k_{p}^{1} - k_{p}^{2}} \right)$$

where k_{p}^{1} and k_{p}^{2} are maximum and minimum principal curvatures

•
$$SI_p = max$$
 of shape indexes and $SI_p \ge (1+\alpha) * \mu$; (convex surfaces)
• or $SI_p = min$ of shape indexes and $SI_p \le (1-\beta) * \mu$; (concave surfaces)
where μ is the mean shape index over neighbours' values and $0 \le \alpha$, $\beta <= 1$

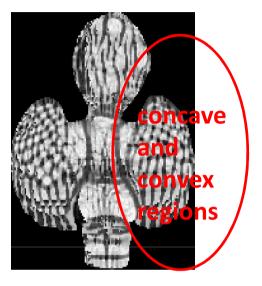
» Invariance to orientation and scale.

Chen, H. and Bhanu, B. "3D free-form object recognition in range images using local surface patches," Pattern Recognition Letters, 28(10), 1252-1262 (2007).



Depth Image

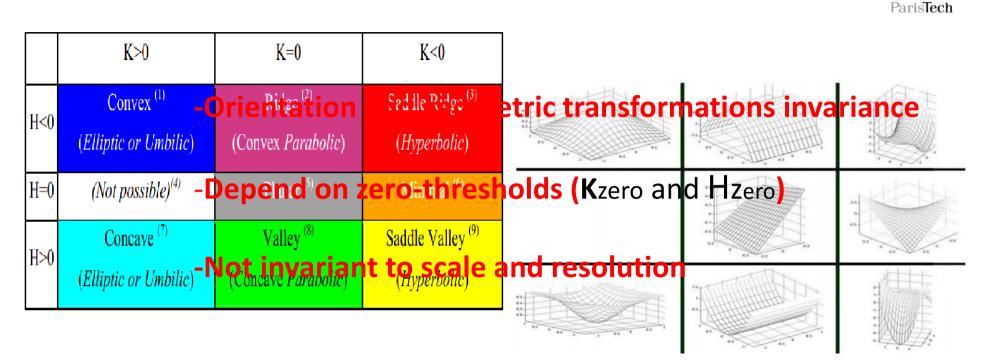




•In SI image: Brighter pixels correspond to the **convex** surfaces (i.e domes and ridge) and darker ones represent **concave** surfaces (rut or cup).

•Details are accentuated on SI image: SI comprises the understanding of the neighbor geometry whereas range image pixel only indicates its depth ->more informative

Shape classification with HK space



	Mean curvature H	Gaussian curvature K				
$T_p = 1 + 3(1 + \operatorname{sgn}_{\epsilon_H}(H)) + (1 - \operatorname{sgn}_{\epsilon_K}(K)),$		$\overline{K \ge 0}$	K = 0	$K \leq 0$		
$\operatorname{sgn}_{\epsilon_x}(X) = \begin{cases} +1 & \text{if } X > \epsilon_x, \\ 0 & \text{if } X \leq \epsilon_x, \\ -1 & \text{if } X < \epsilon_x. \end{cases}$	$H \le 0$	$\begin{array}{c} \text{Peak} \\ T_p = 1 \end{array}$	Ridge $T_p = 2$	Saddle ridge $T_p = 3$		
$\begin{cases} \operatorname{sgn}_{\epsilon_x}(X) = \\ -1 & \text{if } X < \epsilon_x. \end{cases}$	H = 0	None $T_p = 4$	Flat $T_p = 5$	Minimal $T_p = 6$		
pits, peak and saddle surfaces	H > 0	Pit $T_p = 7$	Valley $T_p = 8$	Saddle valley $T_p = 9$		

P. J. Besl and R. C. Jain (1988). Segmentation Through Variable-Order Surface Fitting, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 10, no. 2, pp. 167-192.

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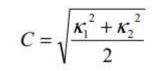


Shape classification with SC shape

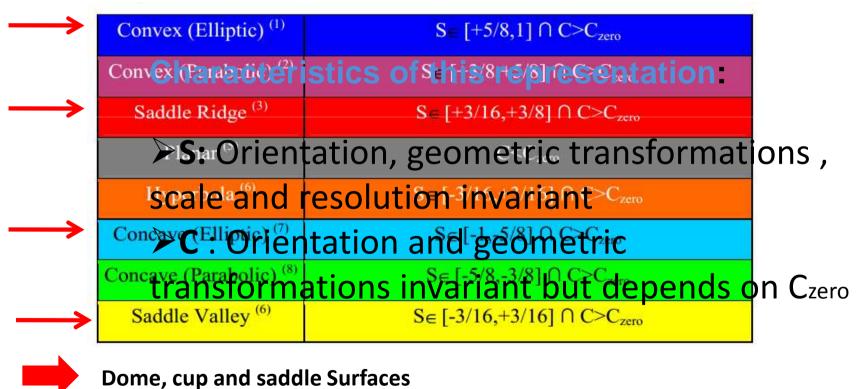
Shape index (S) + curvedness (C) [Koenderink 1992].

$$S = \frac{2}{\pi} \cdot \arctan\left(\frac{\kappa_1 + \kappa_2}{\kappa_1 - \kappa_2}\right) (\kappa_1 > \kappa_2)$$

• defines the shape

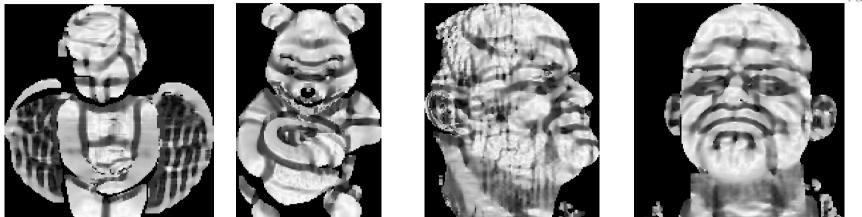


square-root of the deviation from flatness



Shape Index Images





Curvedness Images



•Informative regions are visually strengthen and shape details are accentuated

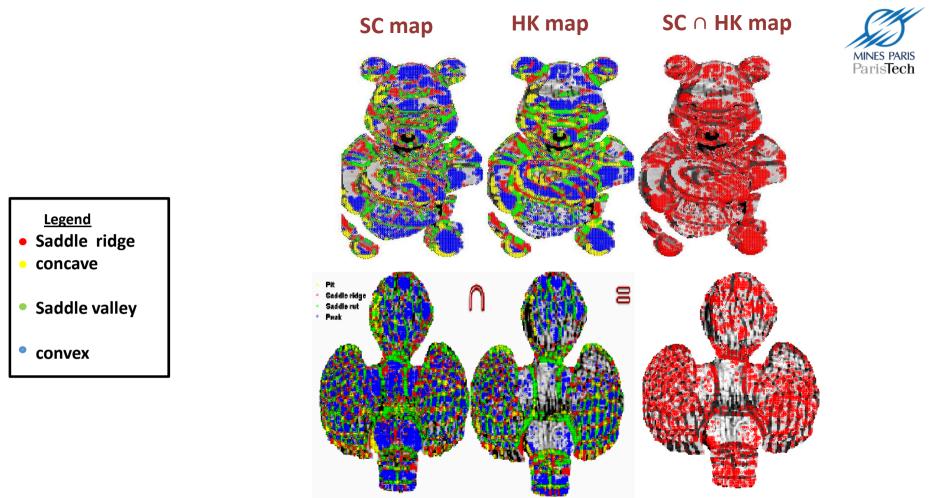
Principle contribution: Classification on the coupled Space HK&SC

Convex (Elliptic) (1)	$H < - H_{zero} \cap K > + K_{zero} \cap S = [+5/8,1] \cap C > C_{zero}$
Convex (Parabolic) ⁽²⁾	$\mathbf{H} \leq \mathbf{H}_{zero} \cap \mathbf{K} \leq \mathbf{K}_{zero} \cap \mathbf{S} \in [+3/8, +5/8] \cap \mathbf{C} \geq \mathbf{C}_{zero}$
Saddle Ridge ⁽³⁾	$\mathrm{H}{<}{-} \mathrm{H}_{\mathrm{zero}} \cap \mathrm{K}{<}{-} \mathrm{K}_{\mathrm{zero}} \cap \mathrm{S}{\in} [+3/16,\!+3/8] \cap \mathrm{C}{>}\mathrm{C}_{\mathrm{zero}}$
Planar ⁽⁵⁾	$\mathrm{H\!<\! H_{zero} } \cap \mathrm{K\!<\! K_{zero} } \cap \mathrm{C\!<\!C_{zero}}$
Hyperbola ⁽⁶⁾	$H \leq H_{zero} \cap K \leq - K_{zero} \cap S \in [-3/16, +3/16] \cap C \geq C_{zero}$
Concave (Elliptic) (7)	$H \succ + H_{zero} \cap K \succ + K_{zero} \cap S \in [-1, -5/8] \cap C \succ C_{zero}$
Concave (Parabolic) ⁽⁸⁾	$H \succ + H_{zero} \cap K \leq K_{zero} \cap S \in [-5/8, -3/8] \cap C \geq C_{zero}$
Saddle Valley ⁽⁶⁾	$H > + H_{zero} \cap K < - K_{zero} \cap S \in [-3/16, +3/16] \cap C > C_{zero}$

Not all regions will be classified: only the common ones

➤ HK ∩ SC: more reliable result

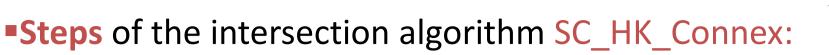
ERDEM AKAGÜNDÜZ , « 3D OBJECT RECOGNITION USING SCALE SPACE OF CURVATURES ", thesis 2011, **12** Department of Electrical and Electronics Engineering



•The combination process assures better saliency.

•Grouping extracted keypoints in a connected components and select the most informative ones by ranking points according to a confidence value on C value.

• reduce the number of selected keypoints





 \geq For each point, extract **neighborhood** N_p (belong to **spherical support** with radius proportional to the surrounding box of the shape)

➢Compute measures of saliency (SC and HK) and extract Keypoints according to the intersection

Compute a **confidence** value for the keypoints (based on **C**)

➢Group detected keypoints with connected components (label = pair of types)

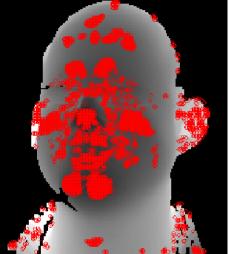
> Extract largest connected components and keypoints with the highest confidence are taken in each components.

Result of SC_HK_Connex detector

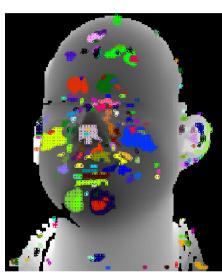


Keypoints without connected components

3118 Kpts



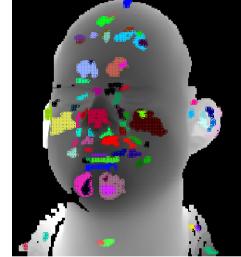
Connected components



Connected components

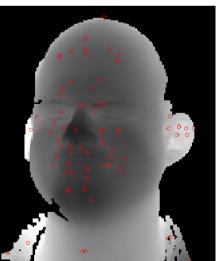
with size > 8 points





Keypoints with connected components

Kpt selection with maximal value of (C) **75 Kpts**



Descriptors



Existing:

■3D SURF descriptor [Jan et al., 10]

 SHOT (Signature of Histograms of OrienTations) and CSHOT descriptor [Tombari and al. ,11]

SHOT: normal estimation based on the Eigenvalue Decomposition of a novel scatter matrix defined by a weighted linear combination of neighbor point distances: definition of a Robust Reference Frame (RF)

✓ Surface normal information is invariant to sampling density, scale and viewpoints.

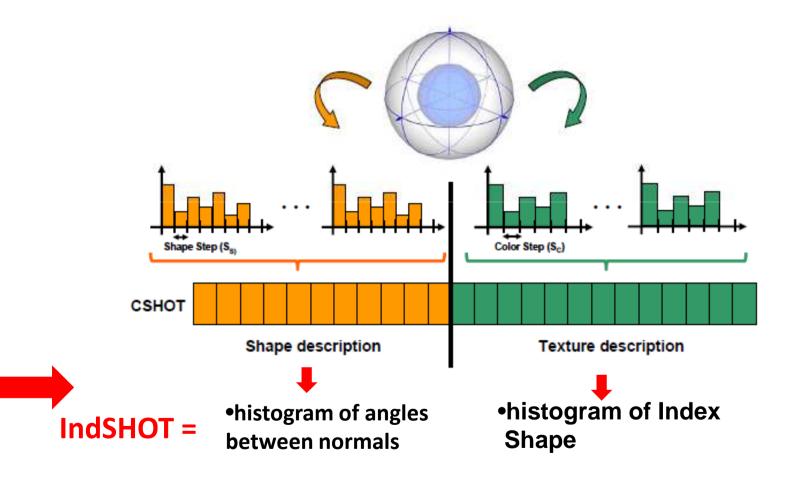
CSHOT: add of texture information

✓ Succeeds to form more robust and descriptive signature



•Proposed descriptor

•IndSHOT Descriptor: joining shape index histogram and histogram of angles between normals





Recognition Task





 Matching: validating the proposed detector and descriptor using a view matching approach

> Similarity measure: Given a test object, we compute a measure of similarity between descriptors extracted on the test view and those of the models in database.

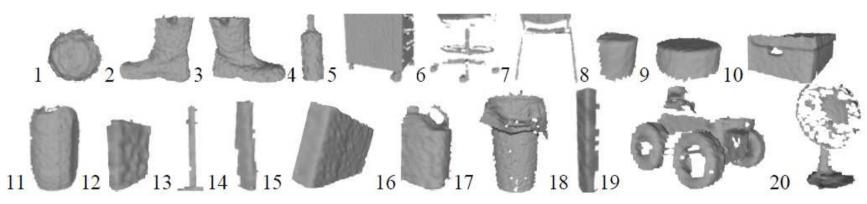
 ✓ For each keypoint , we search for the best nearest neighbor keypoint in the database: Euclidean Distance
 ✓ KDtree to speed up the matching process

Filtering the potential corresponding keypoint pairs based on geometric constraints :

✓ The closest couple of features in term of 3D coordinates distance is the more likely to form a consistent correspondence.

Experimental Results





The 20 objects of our lab-Dataset (4 to 15 views/object)



Examples of objects from the RGB-D Dataset *(46 common household objects, 25 views/object)

• Evaluate our detector and descriptor in terms of recognition rate

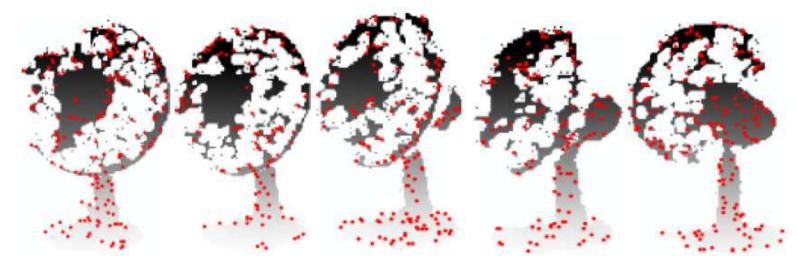
* http://www.cs.washington.edu/rgbd-dataset/

Keypoint detection





SI detector SC_HK SC_HK_Connex



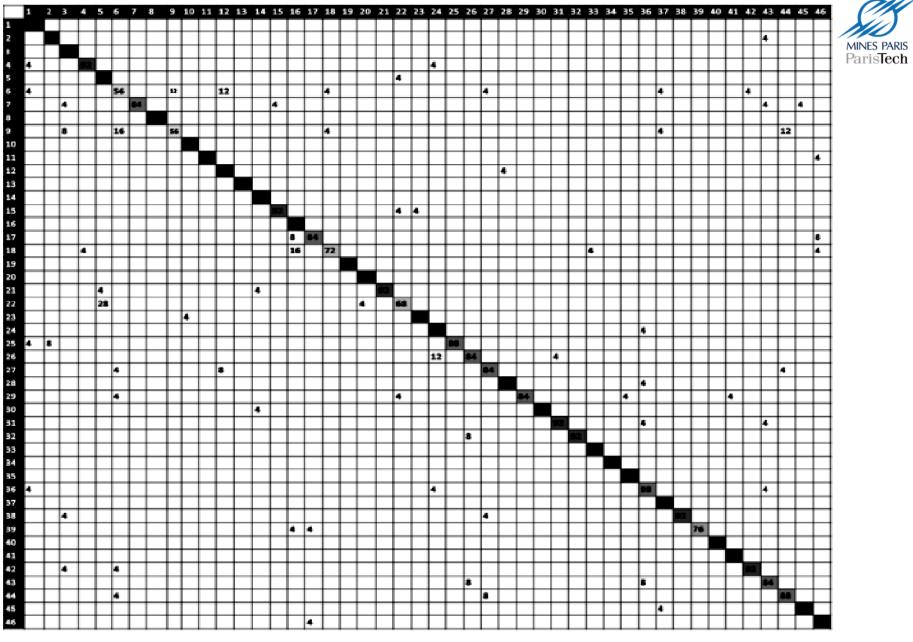
Detected keypoint on fan model, with SC_HK_connex, in view angle variation

Recognition rate



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	100																			
2		96																		
3			100																	
4	4			92																
5					96															
6	4					56			12			12						4		
7			4				84								4					
8								100												
9			8			16			56									4		
10										100										
11											96									
12												96								
13													100							
14														100						
15															92					
16																100				
17																8	84			
18				4												16		72		
19																			100	
20																				100

Confusion matrix for the result of SC_HK_connex+IndSHOT methods on Lab-dataset



Confusion matrix for the result of SC_HK_connex+IndSHOTmethod on RGB-D object dataset



Recognition rates

	IndSHOT	SHOT	CSHOT			IndSHOT	SHOT	CSHOT		
					SID	89.06%	70,75%	77.77%		
SC_HK	82.5%	62,5%	67.5%		SC_HK	91.12%	75,28%	82.14%		
0	n Lab-datas	et		-	RGB-D object dataset					

•The overall recognition rate is quite promising for the SC_HK_Connex

Computation time for our recognition process (detection + description + features matching) is quite low (~0.7s) for 100 Keypoints

Conclusion



- ✓ A new 3D detectors based on combination of surface classification criteria
- Combined descriptor IndSHOT: shape index and angles between normals
- ✓ Recognition rate of 91.12% on public Kinect dataset (RGB-D object dataset)
- Evaluation on other databases
 Evaluation of scale invariance and noise robustness



Thank you for your attention

