Semantic Principal Curvature (SPC)

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Outline

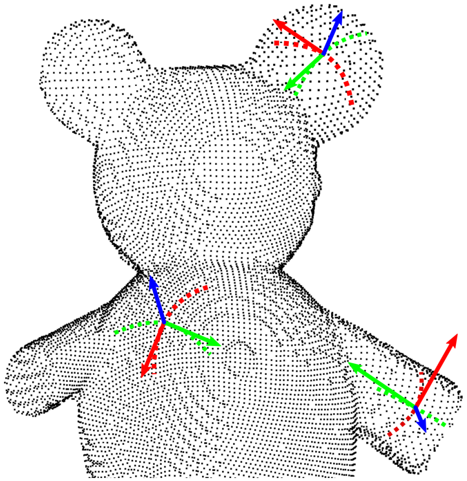
- Position of the problem
- Principal Curvatures (not Gaussian Curvature)
- Histogram: aggregation of the curvatures
- Metric
- Results
- Discussion, Conclusion

Motivation

- 3D sensors are more and more popular, Kinect, Lidar, etc
- In some conditions like by night, it is difficult to recognize an object based on colors
- Recognition of an object based on the Point Cloud and rotation-translation invariants
- Some algorithms exist that are local. Here we propose a **global** approach.
- Gestalt Principle: *Perception of the overall shape emerges from individual stimuli*

Principal curvature

- Principal curvature K1 and K2
- Second order description of a surface
- Local
- Invariant
  - Translation
  - rotation
- Different from Gaussian curvature [K1;K2] not K1xK2



Second order fit of the Neighborhood

- The curvature is based on a neighborhood

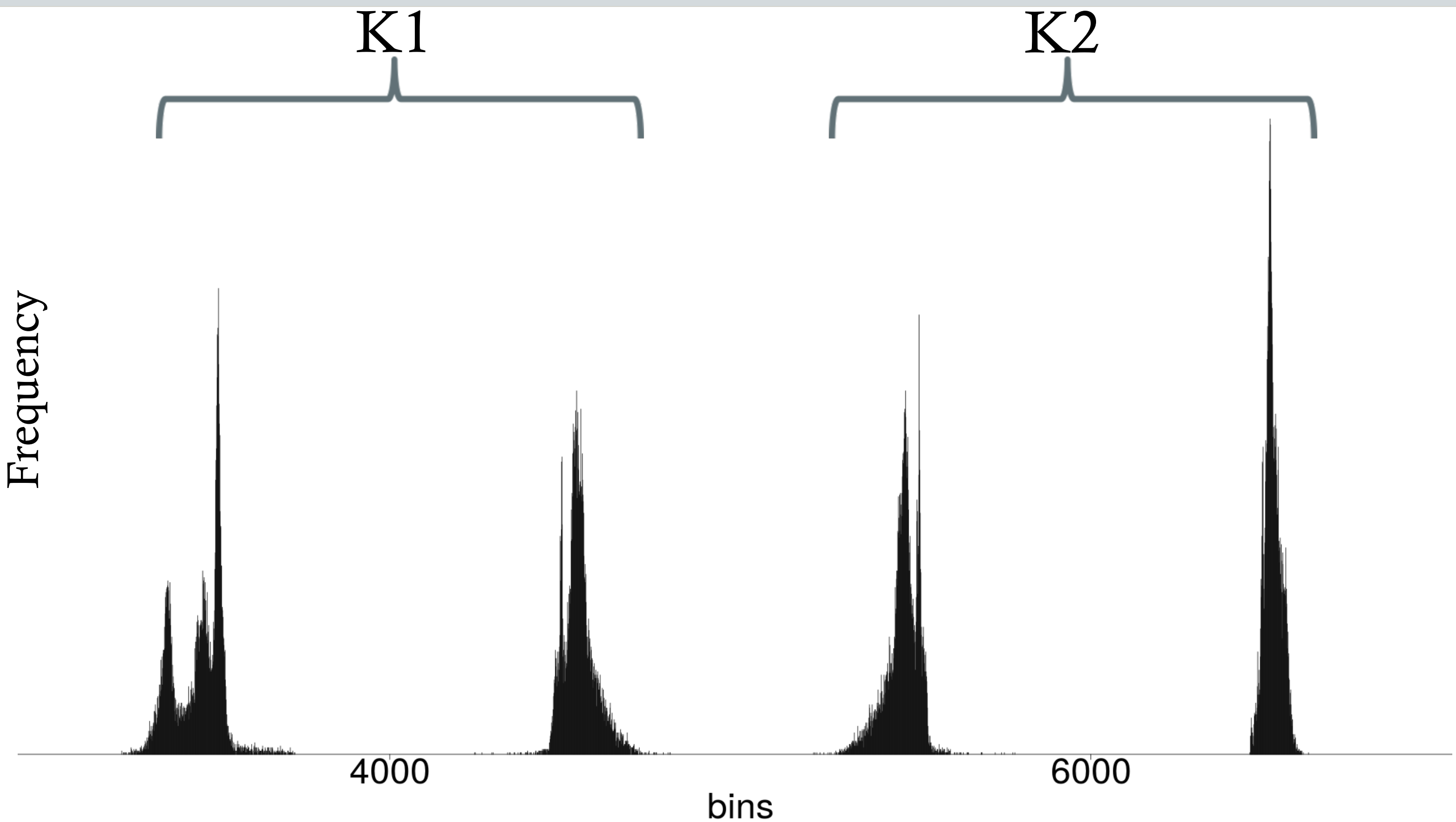
$$r_\lambda = \lambda \cdot \underbrace{\max_{p,q}(\|v_p - v_q\|_2)}_{\text{max distance, } M}, \ \lambda \in [0;1]$$

$$B(v_i, r_\lambda) = \{p \in \mathbb{R}^3 \mid \|v_i - p\|_2 \leqslant r_\lambda\}.$$

- Polynomial fit (2^{nd} order) on the neighboring points

$$\varepsilon = \sum_{v_k \in B_{v_i,\lambda}} \left(J_{i,n}(v_k) - z(v_k)\right)^2$$

Principal Curvature Histogram



Signature of an object, concatenation of the First Principal Curvature (K1) histogram and the Second Principal curvature (K2) histogram

Metric

- The signature is first normalized
- Distance chosen is the Khi^2 distance

$$d_{\chi^2}(\mathtt{A},\mathtt{R}) = \sum_j \frac{(H_{\mathtt{A}}(j) - H_{\mathtt{R}}(j))^2}{H_{\mathtt{A}}(j) + H_{\mathtt{R}}(j)}$$

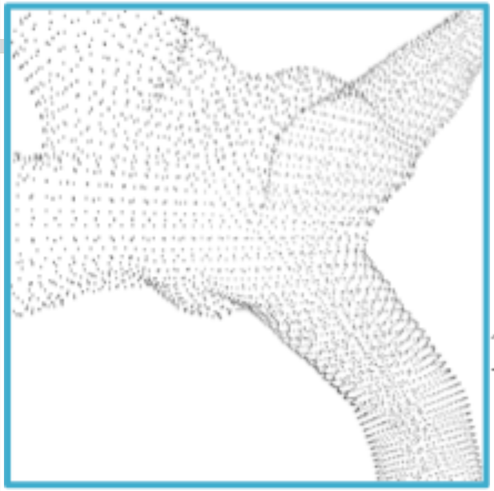
- Khi^2 distance good metric for the distance between 2 histograms

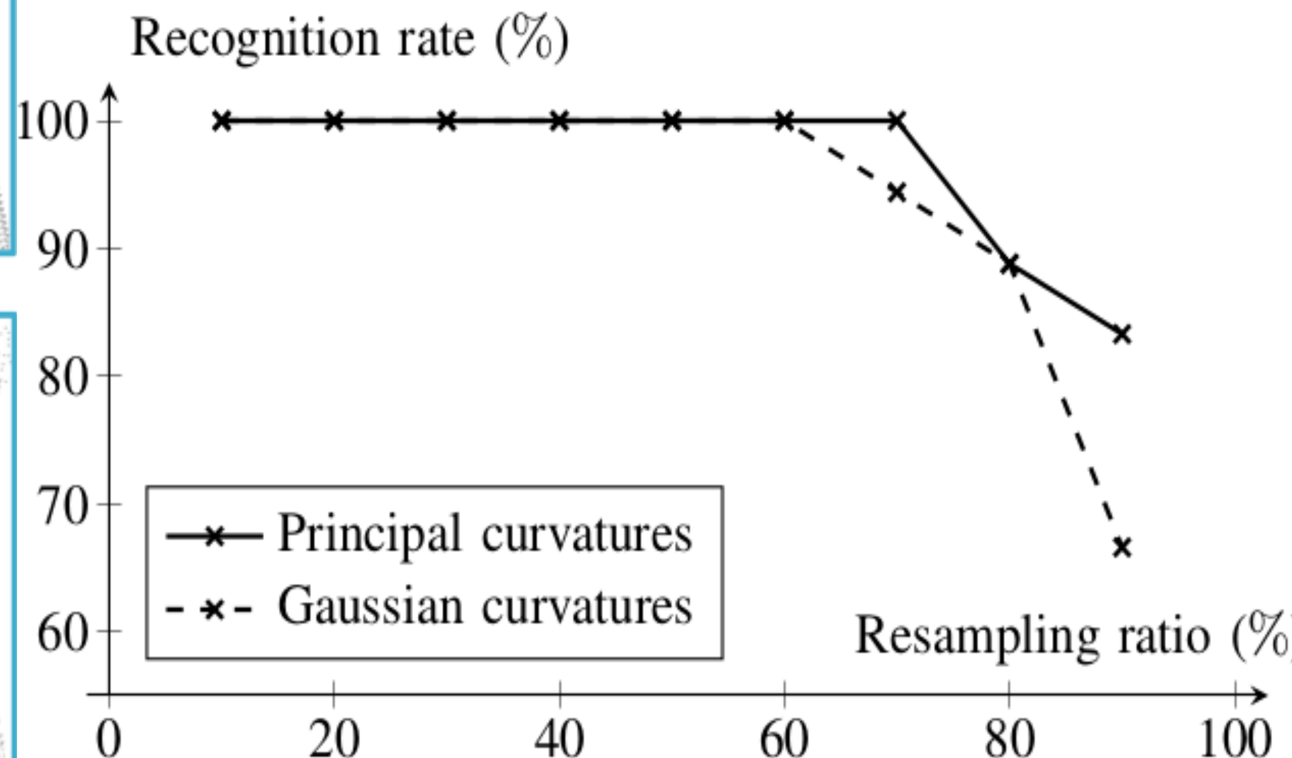
Objects to recognize

Realistic corruptions of Point Clouds

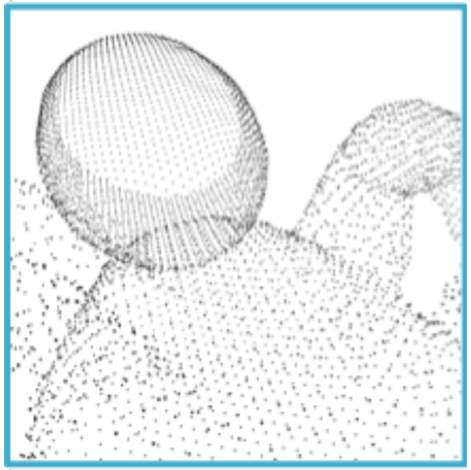
- Noise related to
  - quality of the 3D sensors
  - distance of acquisition
  - light condition
  - material of the observed objects
- Down-sampling: related to sensor resolution
- Occlusions
  - in a real scene an object can be occluded by another object
  - in some case the object in seen from only one point of view.

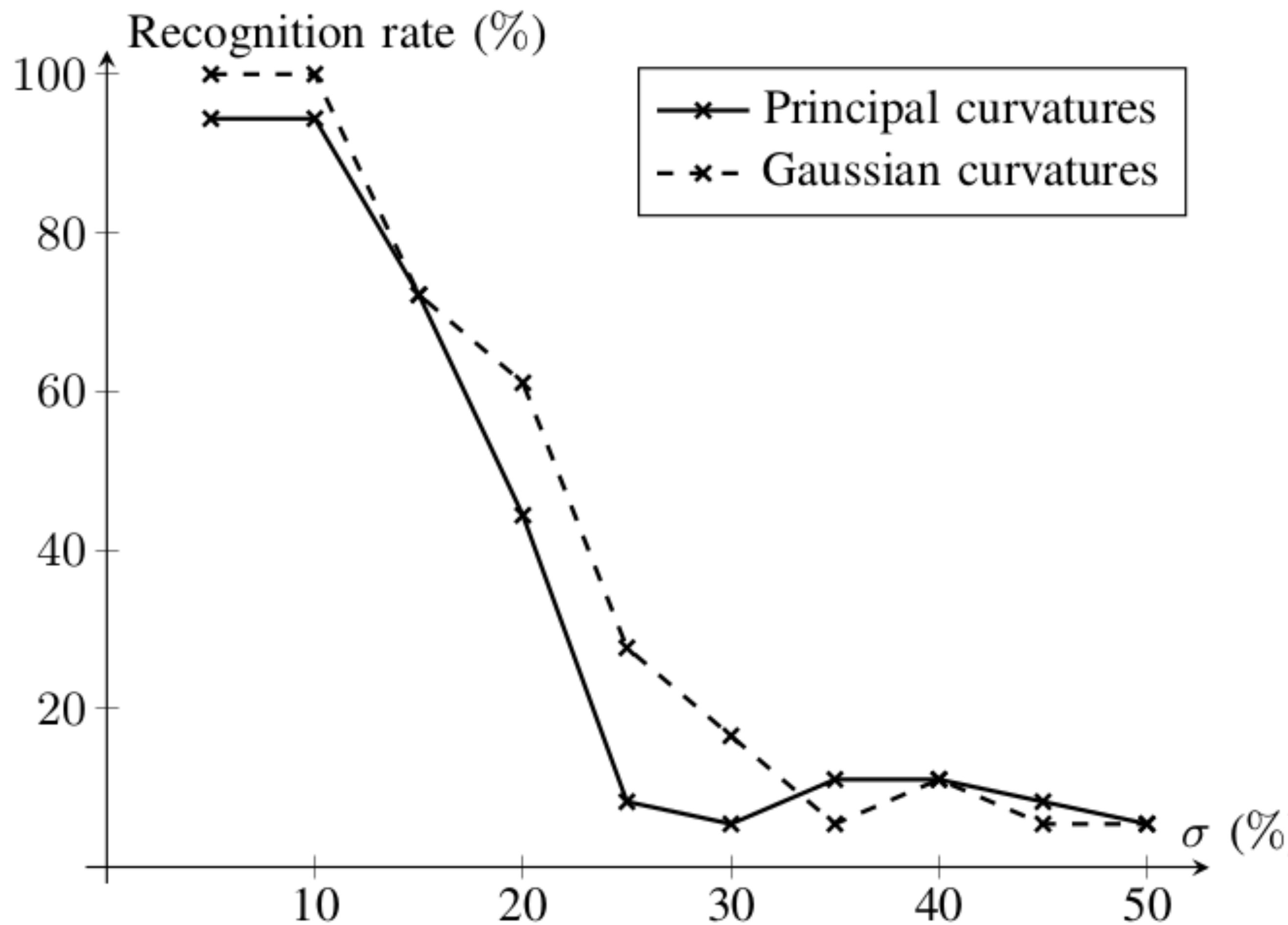
Resilience to down-sampling



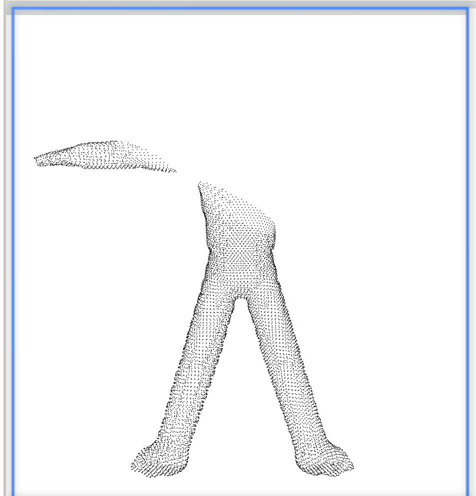


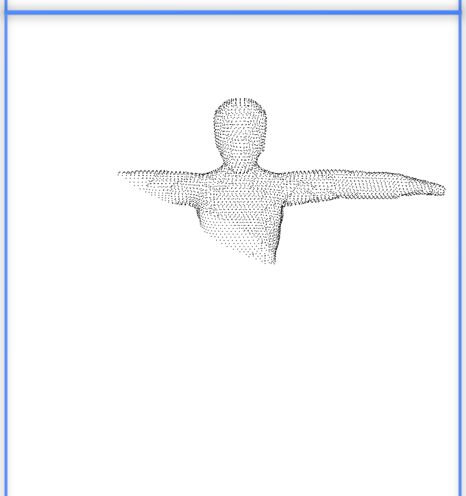
Resilience to noise

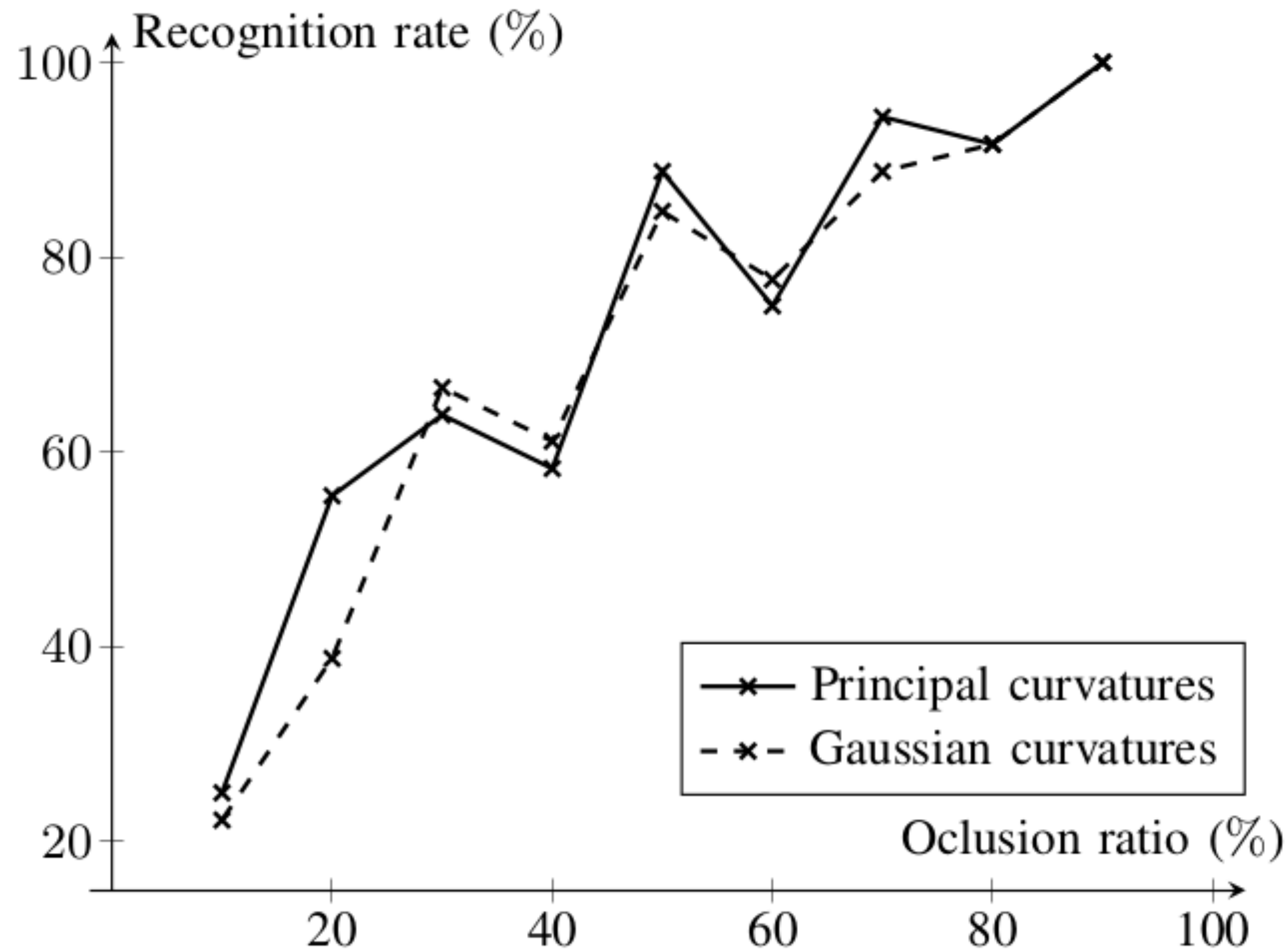




Resilience to occlusion (20%)







Discussion, Conclusion

- Our method provides good results for occlusions, noise and down-sampling
- Easy to implement
- Compared to local methods (key points) our method is more robust in noisy conditions
- Combined with Lidarbox (Razali & Ouarti, ICIP 2017), possibilities to segment and to classify.

Questions?