Seminar in Robotics for CSE
"GPU-based feature matching"

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[1]CSE D-MATH, [2]ETH Zurich and [3]Sevensense Robotics AG

16.09.2020

Introduction

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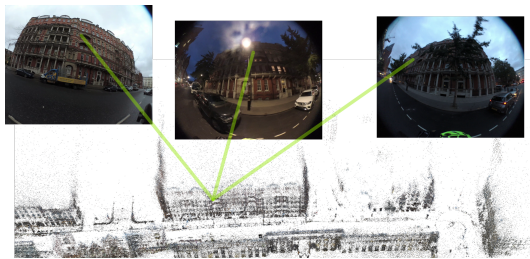

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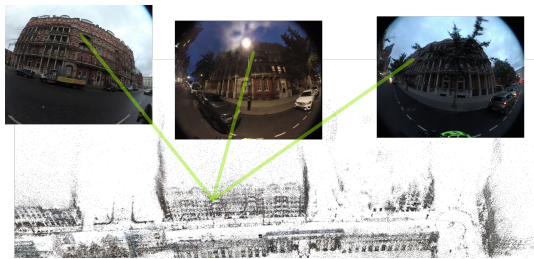

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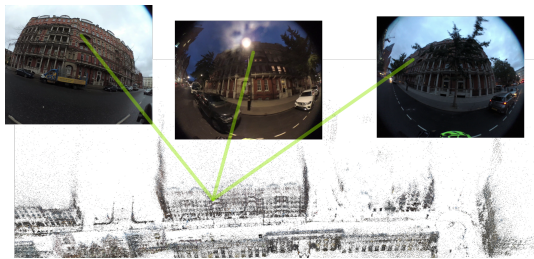

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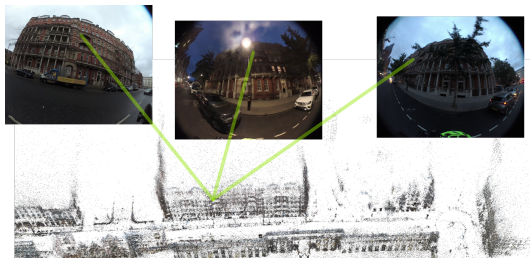

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- However, in some applications the crucial role plays the efficiency, latency and adaptability of the system.
- The modern rise of GPUs provides the way to achieve these goals.

Literature review

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And specifically, how to use GPU for efficient matching?

How to obtain descriptors?

Philosophy of feature detection and description

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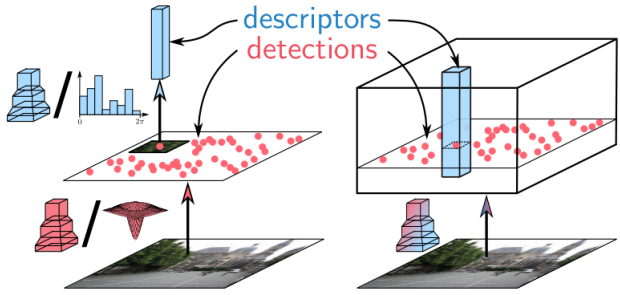
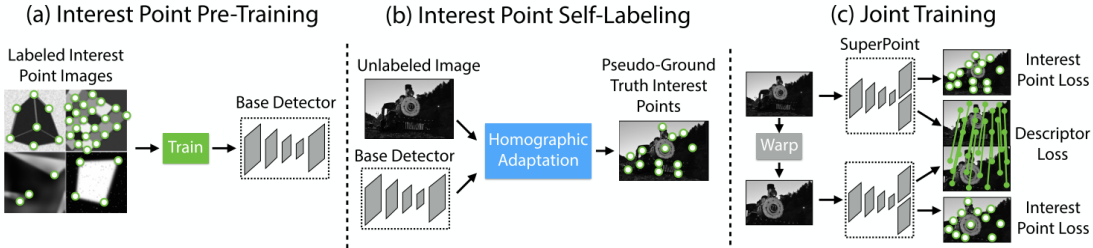


(a) detect-then-describe (b) detect-and-describe

Feature detection and description

Feature detection and description

SuperPoint[1] idea: to pretrain feature detector on artificially warped geometric objects.



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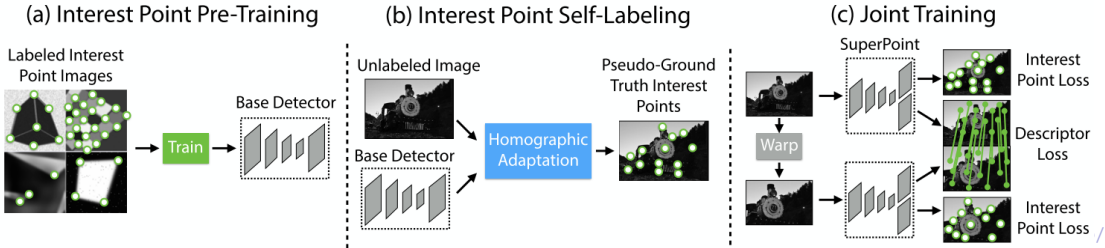

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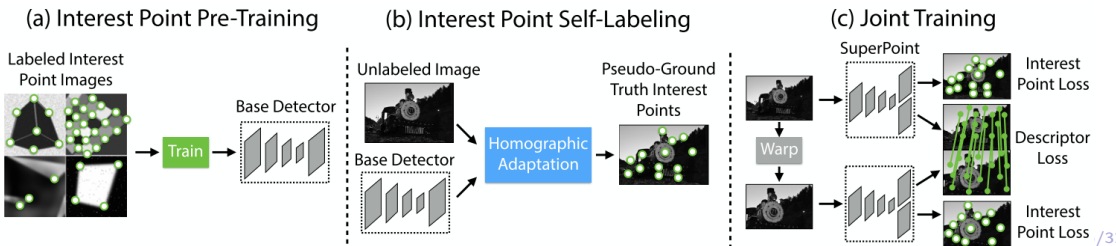

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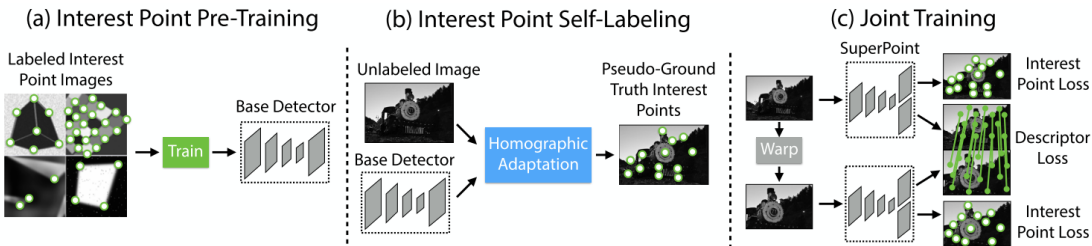

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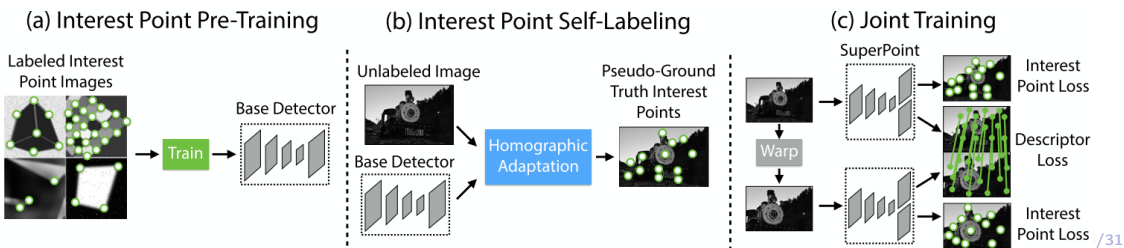
– Training on artificial examples introduces bias towards detecting planar geometric structures and is worse for the real world images.



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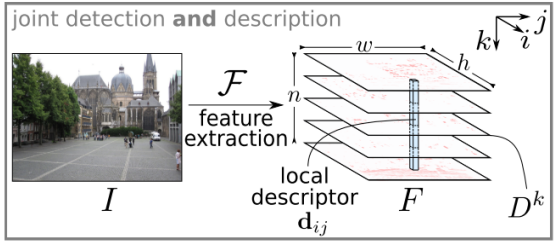
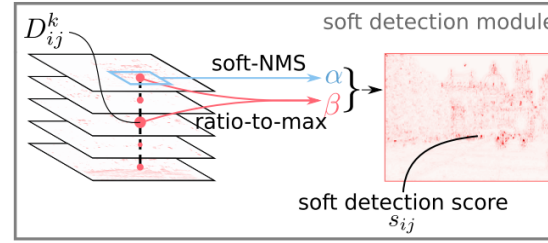
D2–Net[2] idea: joint detection and description pipeline.





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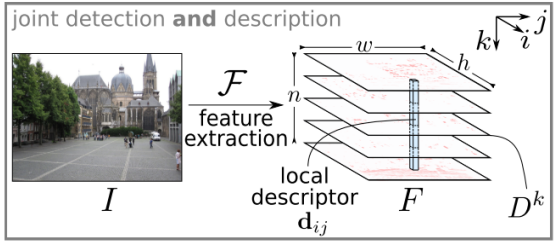

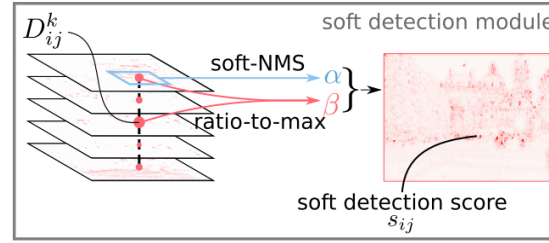

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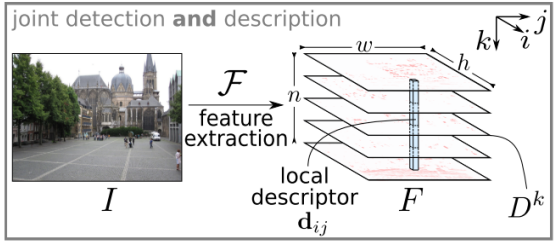
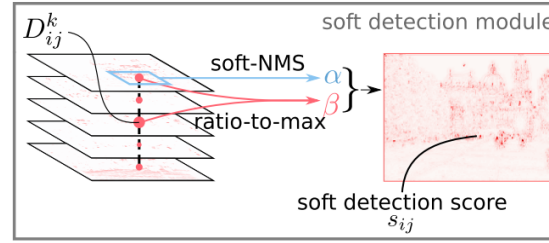
– Predicts properties of keypoints in rather empiric conventional fashion (softmax, non-maximum suppression among descriptors).





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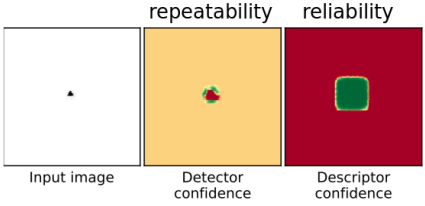
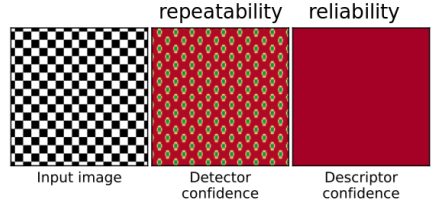
R2D2[3] idea: estimate separately reliability and repeatability of descriptors





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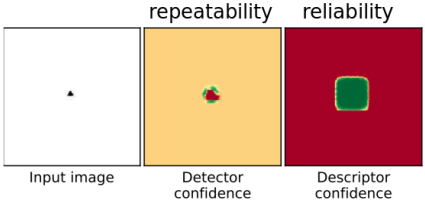

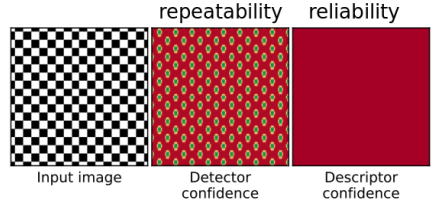

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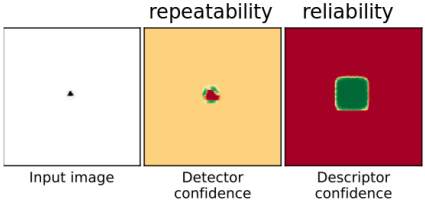

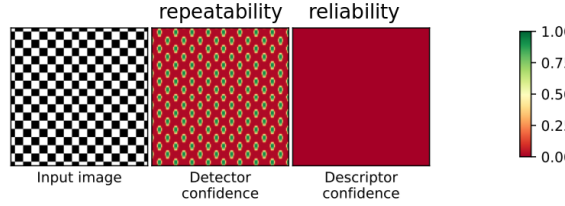

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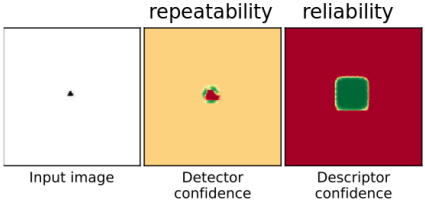
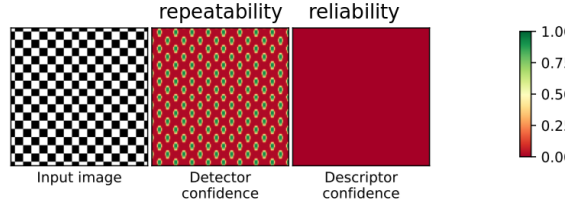
– Needs the choice of higher number of hyperparameters.





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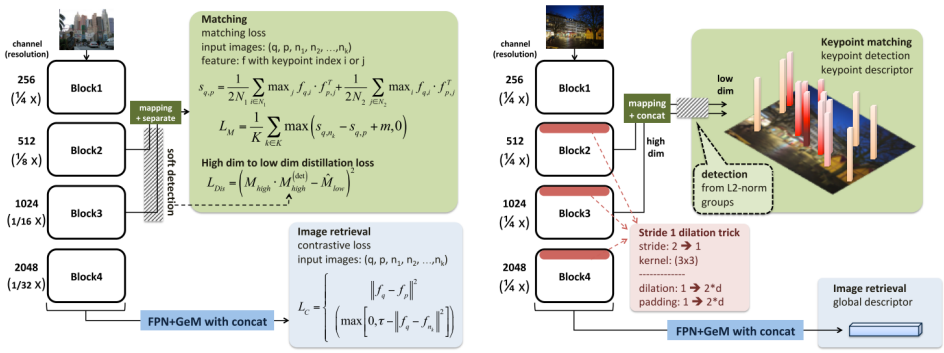
UR2KiD[4] idea: multi-task for local (patches) and global (image retrieval) description.



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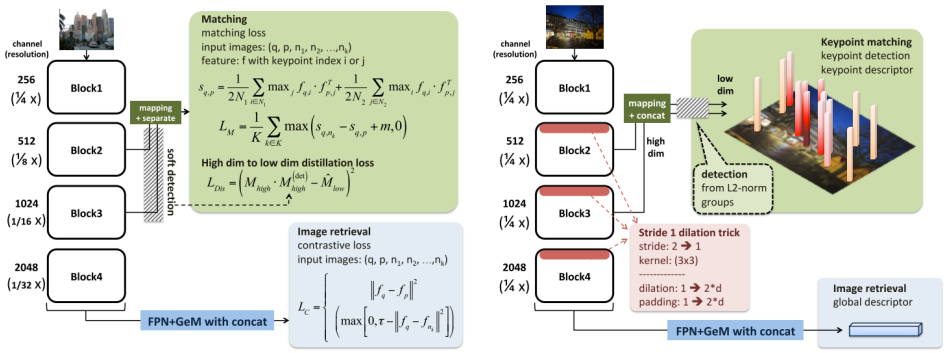

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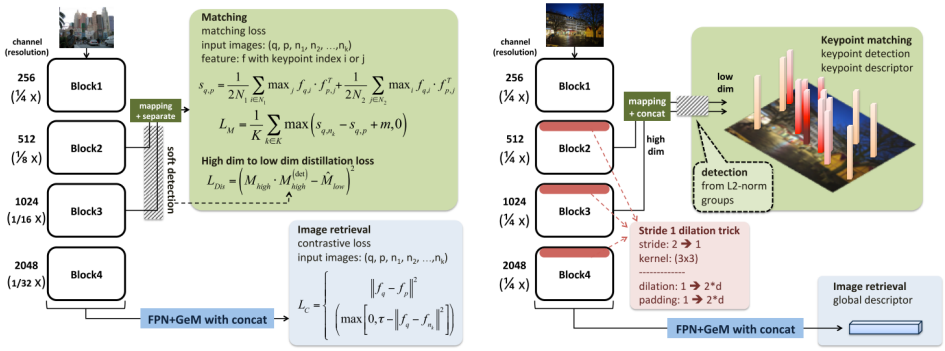
+ Is more robust against appearance and scale changes than the previous methods.
+ Its idea of multi–task learning leads for the improvement in both tasks and could be useful in the future constructions of weakly supervised but powerful networks.



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We observed descriptors construction.

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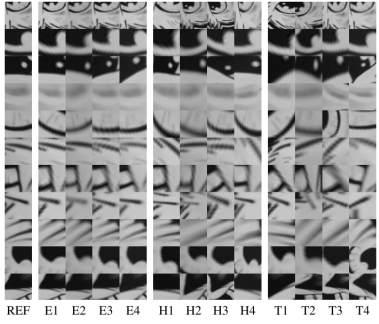
How to measure their quality?

Descriptors quality assessment

HPatches[5] — dataset for **2D–2D matching** assessment.
Consists of extracted and augmented with noise and transformations patches from various image sequences in varying lightning conditions and camera positions.



[5] Balntas et al., "HPatches: A benchmark and evaluation of handcrafted and learned local descriptors", Apr. 2017.

Descriptors quality assessment

The Long–Term Visual Localization Benchmark[6] consists of several datasets of scenes under different appearance conditions for the **2D–3D** problem of estimating the 6 DoF camera pose.

[6] *The Visual Localization Benchmark, www.visuallocalization.net.*

We observed how to construct good descriptors.

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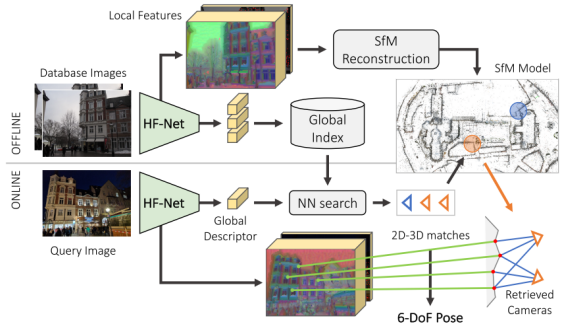
How to match them finally?

Matching of features

Hierarchical Feature Network[7] idea: coarse-to-fine pose estimation with distillation.



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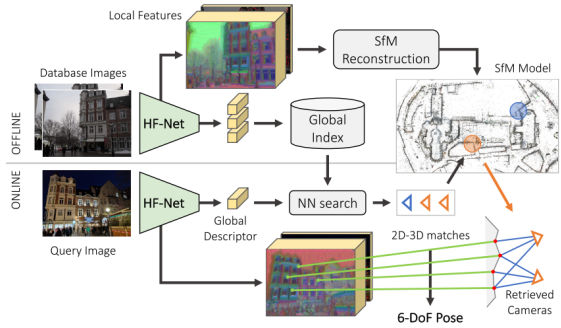

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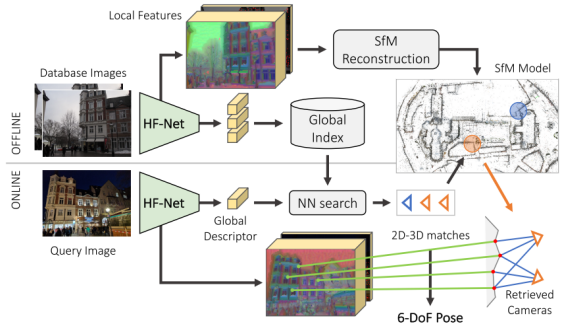

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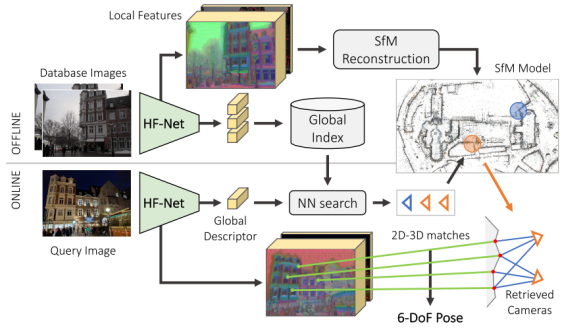

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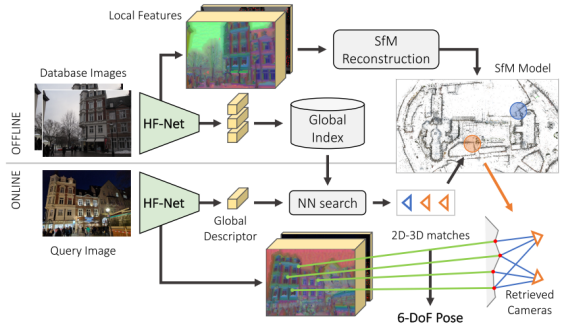
- \+ Distillation allows to improve the method using the global teacher signal.
- \+ Simultaneously estimates the camera 6-DoF pose.
- ± Tailored for mobile low computational power applications.



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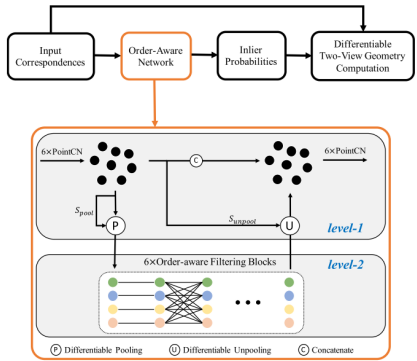
Order–aware network[8] idea: use local context and feature permutation invariance.



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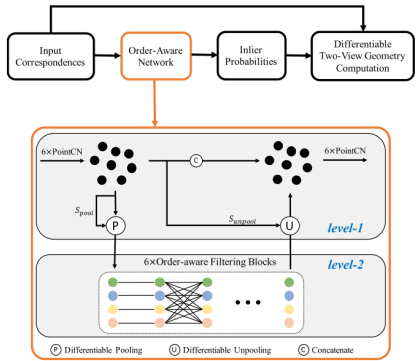

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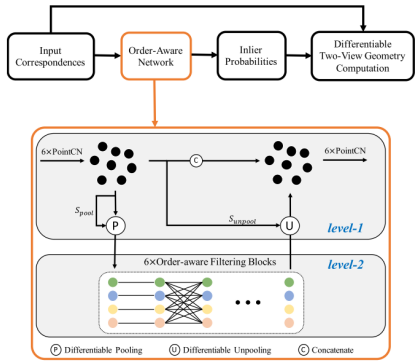

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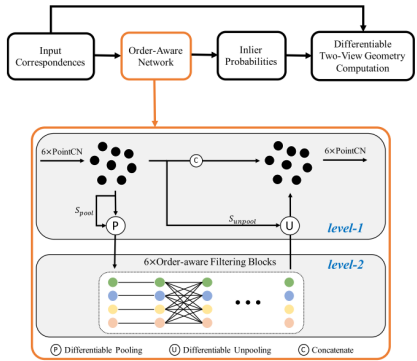
+ Captures both global and local context.
– Relies heavily on the quality of descriptors, as it is an outlier–rejection network uses the nearest–neighbor search.



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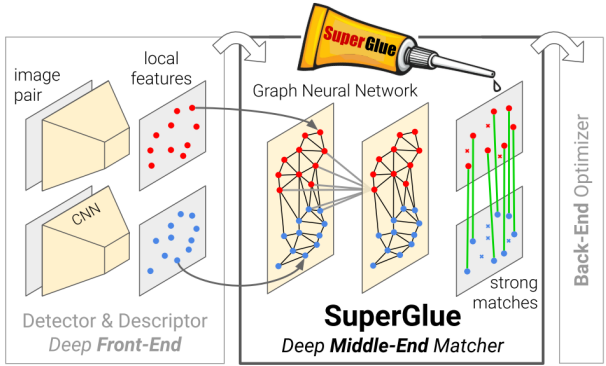
Matching of features

SuperGlue[9] idea: use a graph neural network and attention to solve an assignment optimization problem.



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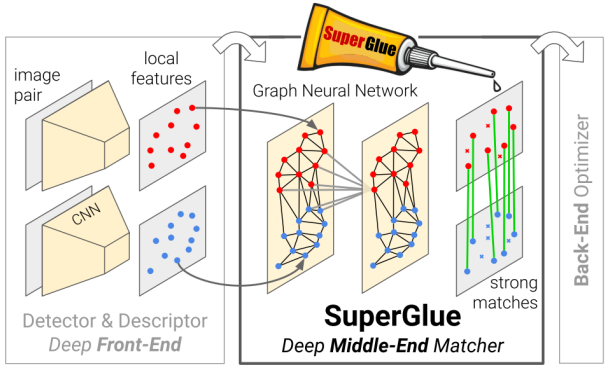
+ Achieves significant improvement over existing approaches, working real–time and well both with learned and traditional features.



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How to leverage GPU for more efficient matching?
(e.g. with huge databases)

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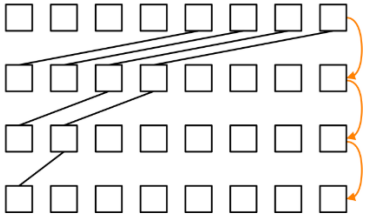

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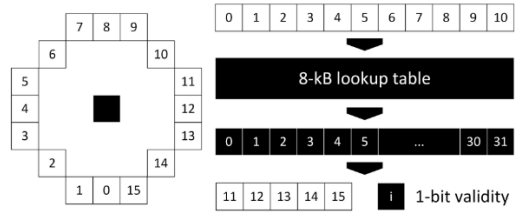

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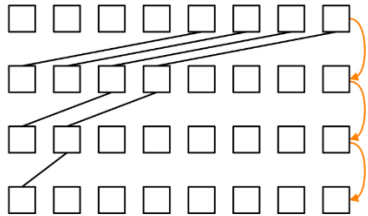

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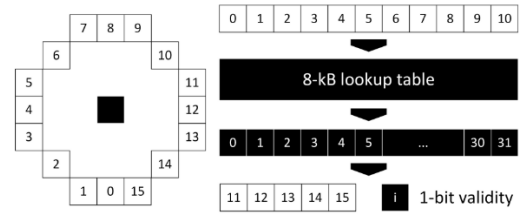

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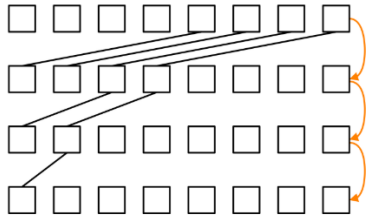

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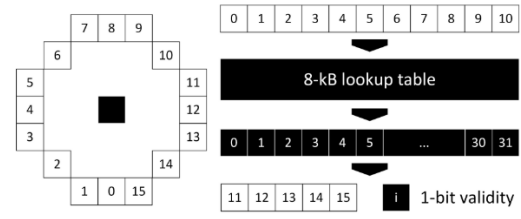

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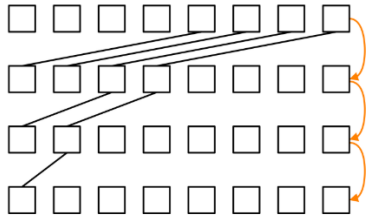

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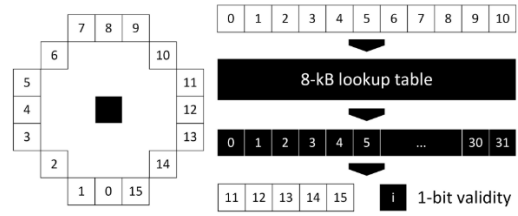

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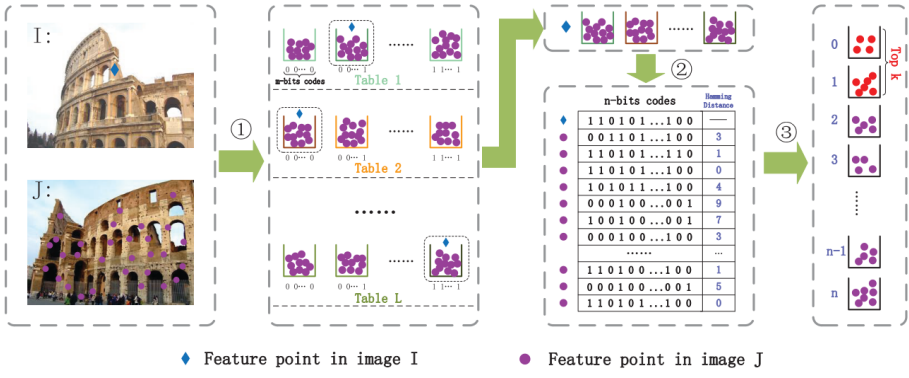

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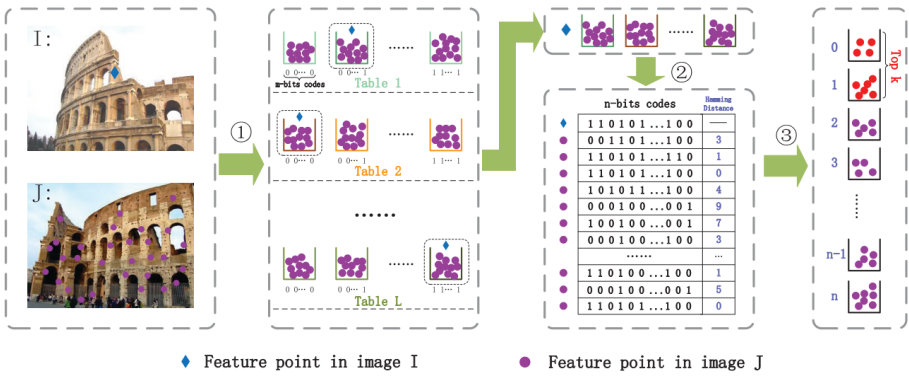

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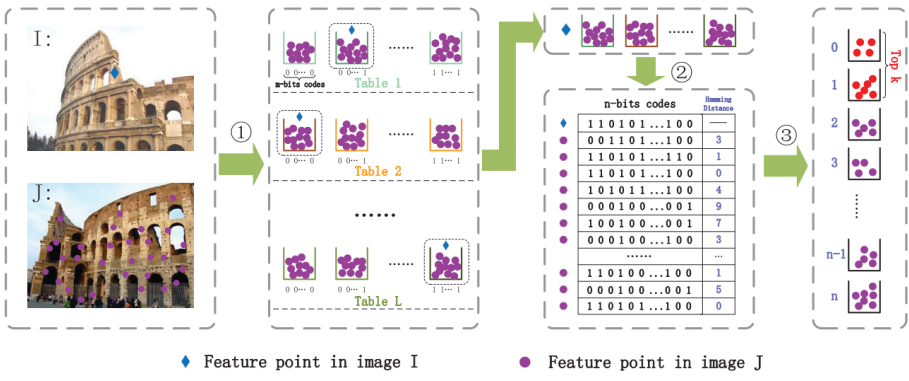

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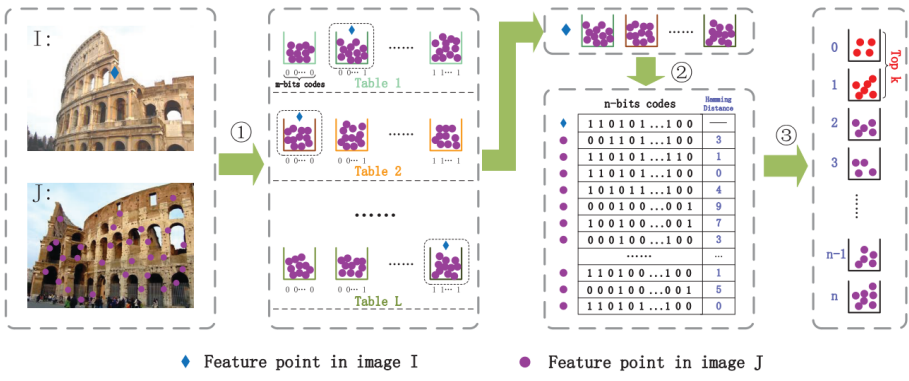

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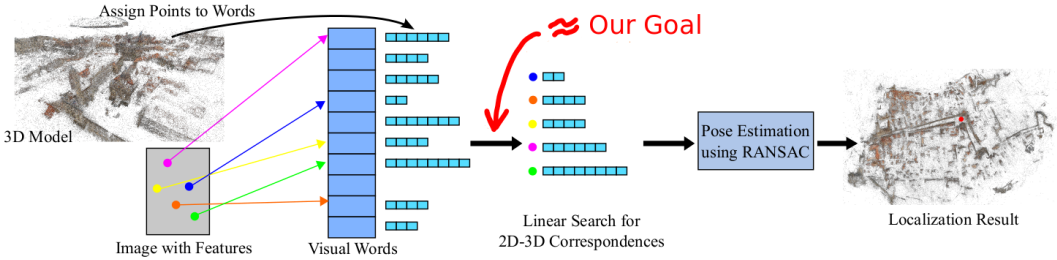

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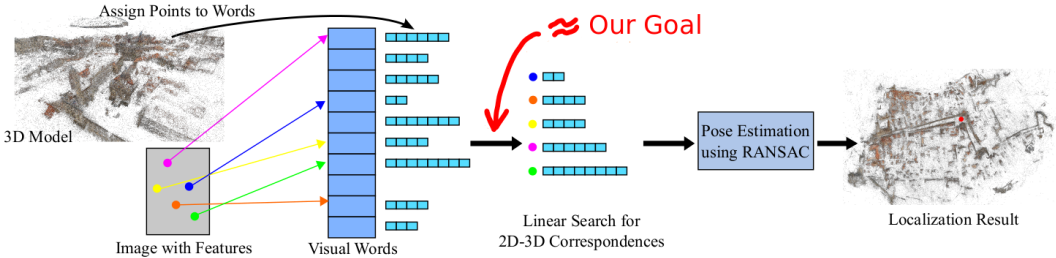

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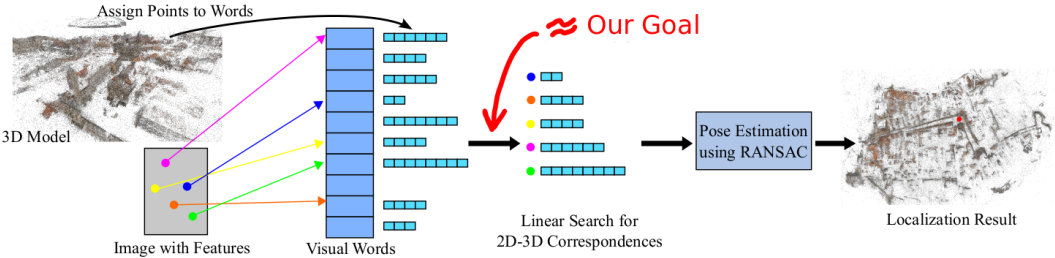

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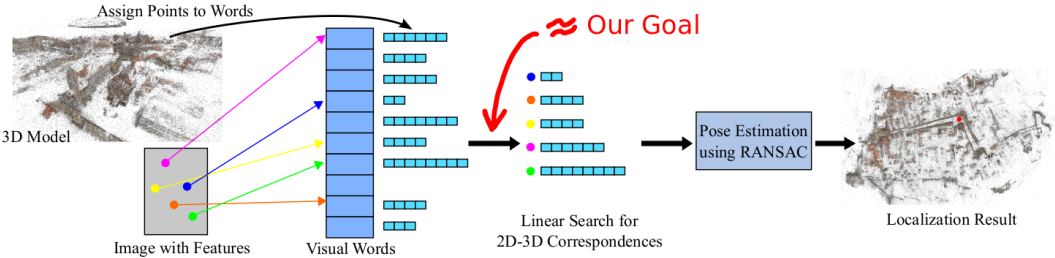

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Goal: find the closest descriptor in DB (in Euclidean metric) for each one in the query.

Methods compared

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   For these two methods we use empirically the most reasonable parameters.

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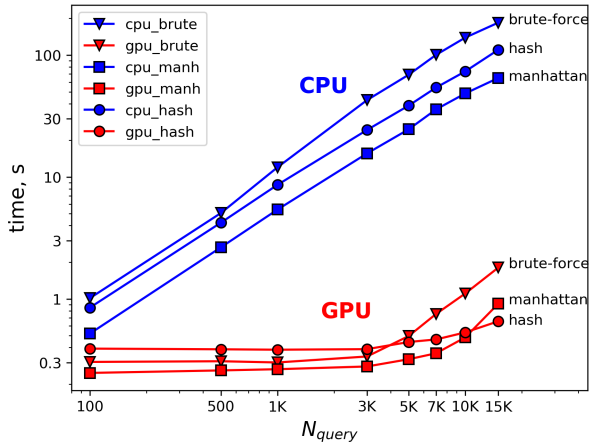
Time depending on algorithm, machine and **query** size ($N_{\text{db}} \approx 28\text{K}$)



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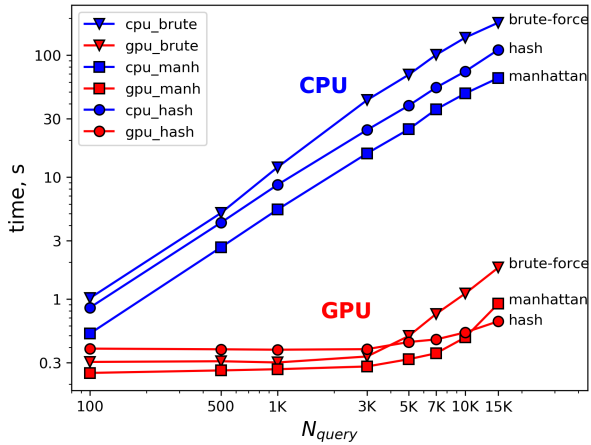

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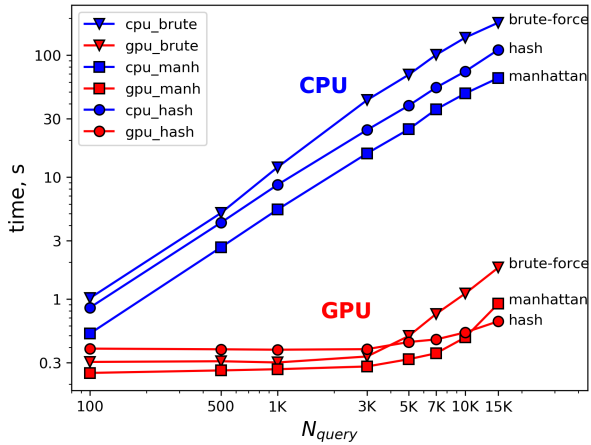

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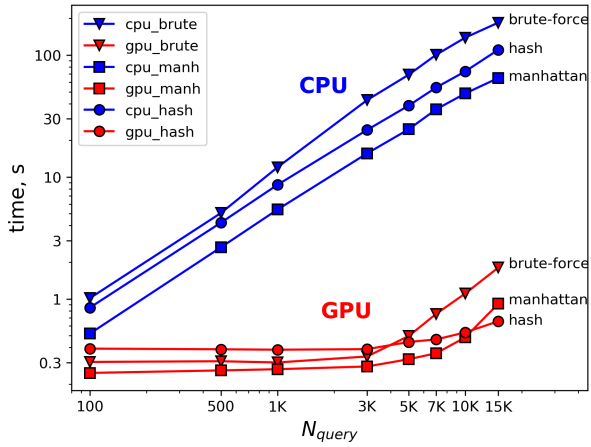

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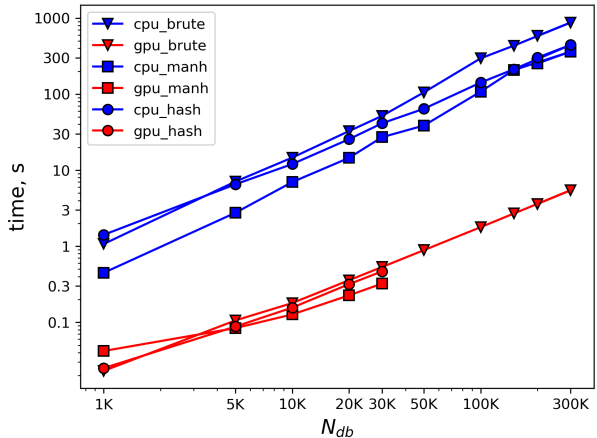
- Possible explanation for blow-up of GPU with big queries - GPU memory overload.

Sweep over different DB sizes with constant query ($N_{\text{query}} = 5\text{K}$)



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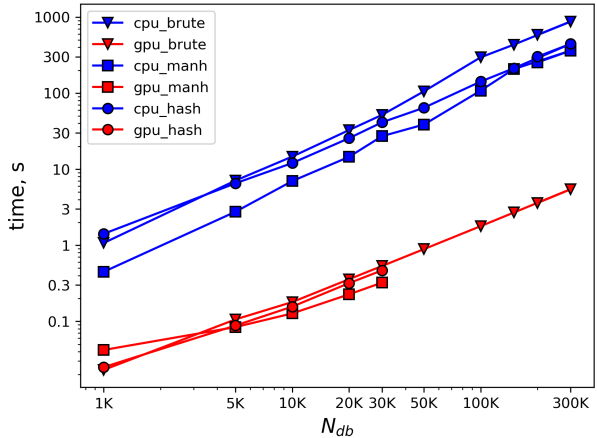

- Perfect linear time dependency for both CPU and GPU, as expected.

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Questions?

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How to find the best parameters? Which quality metric to use?

Metric of quality is the average Euclidean distance ("dist") in corresponding pairs.

t, s	dist	Parameters			
		L	tableSize	M	W
0.496	**0.596**	ref. GPU brute–force			
0.492	0.602	3	17	1	0.5
0.443	0.624	3	37	1	0.1
0.254	0.654	1	83	3	0.5
0.172	0.678	1	83	3	0.1

Table 1: Example of dependence of results on the parameters of the method, for LSH

Results for $N_{\text{query}} = 5000, N_{\text{db}} = 28188$

Type	Mode	Av. dist	t, s	std(t), s	std(dist)	CPU/GPU
Brute-force	CPU	0.595	46.133	0.023	0	~ 80
	GPU		0.496	0.003	0	
Manhattan	CPU	0.608	24.632	2.585	0.066	
	GPU		0.32	0.01	0.066	
LS Hashing	CPU	0.623	38.562	2.077	0.066	
	GPU		0.439	0.006	0.066	

Table 2: Comparison of methods with the empirically best parameters

"Best" taken parameters:
for Manhattan: $M = 1, W = 1$,
for LSH: $L = 3, tableSize = 83, M = 1, W = 0.1$.

References

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