

Efficiency Aware Multi-Technique Visual Place Recognition

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What Is VPR?

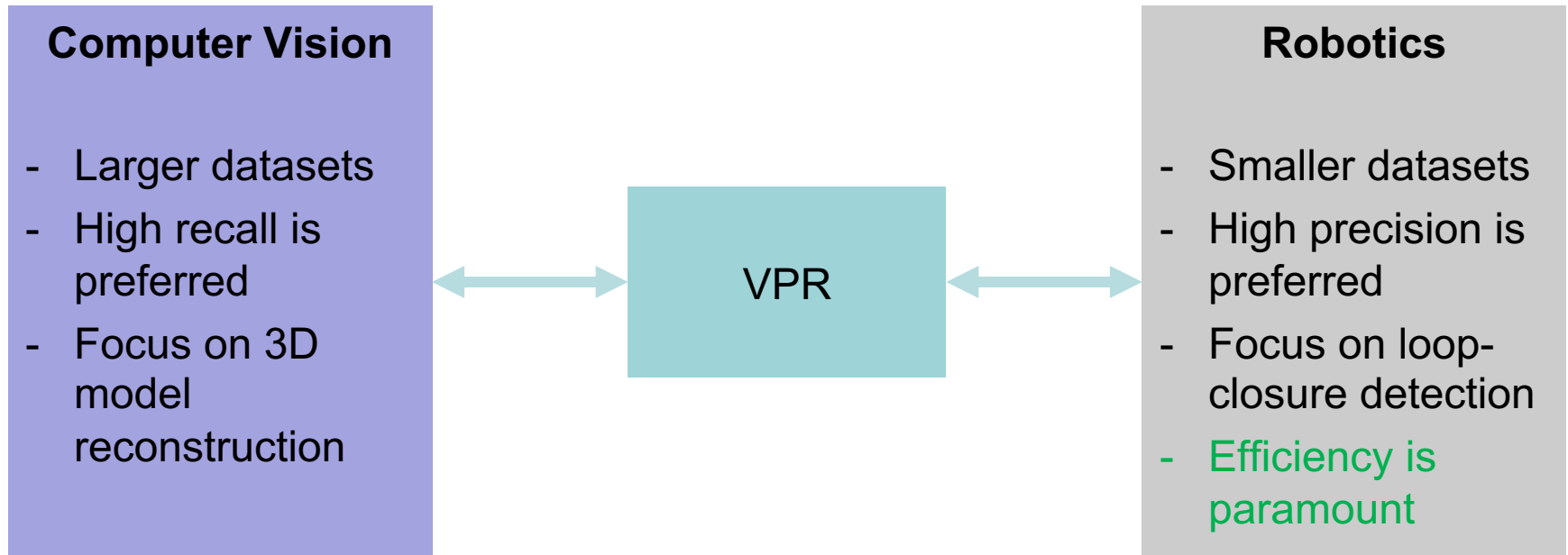
- **Definition: the ability for a system to recognize a previously seen place using only image information**

Current observation



Internal database





Why Is VPR Challenging?

Visual changes

- Same place can look very different
 - Day/night cycles
 - Seasonal changes
 - Different viewpoints
 - Dynamic elements
- Two places can look the same
 - Especially in the same environment

Seasons



Viewpoints



Occlusions,
Dynamics

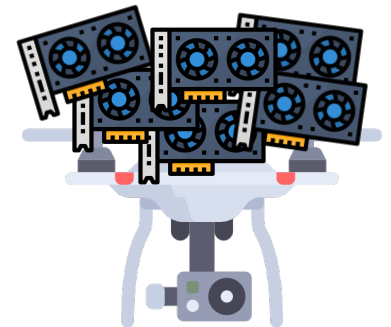


Weather,
Lighting,
Shadows

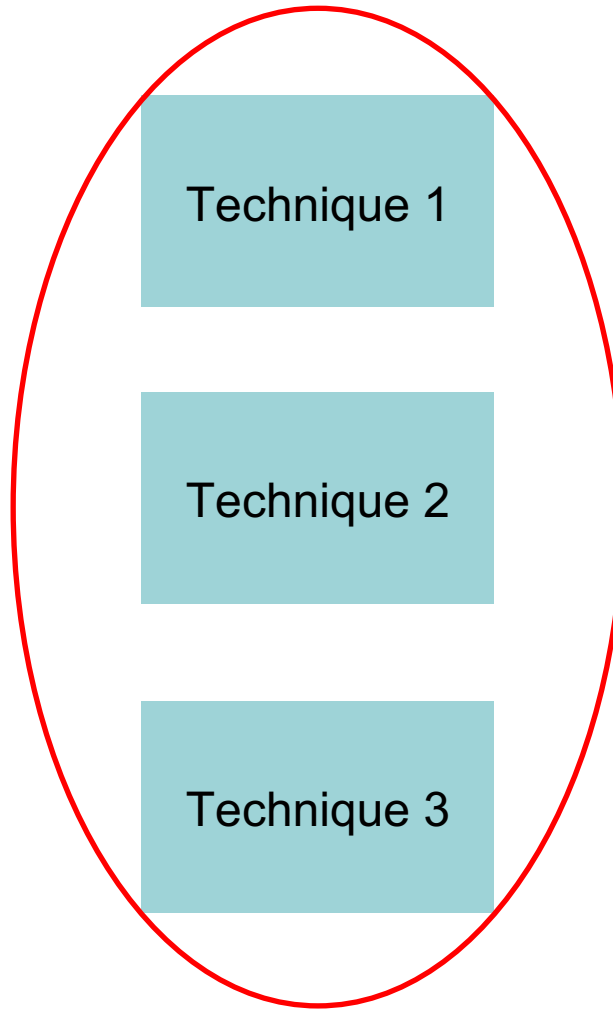


Computational requirements

- Mobile robotics often operate with low-end hardware
- How to efficiently represent an image for matching?
- How to search an ever growing internal image database?



Several Specialist Techniques



Pros

- Viewpoint
- Efficient

- Appearance

- Viewpoint
- Appearance

Cons

- Appearance

- Viewpoint

- Very expensive

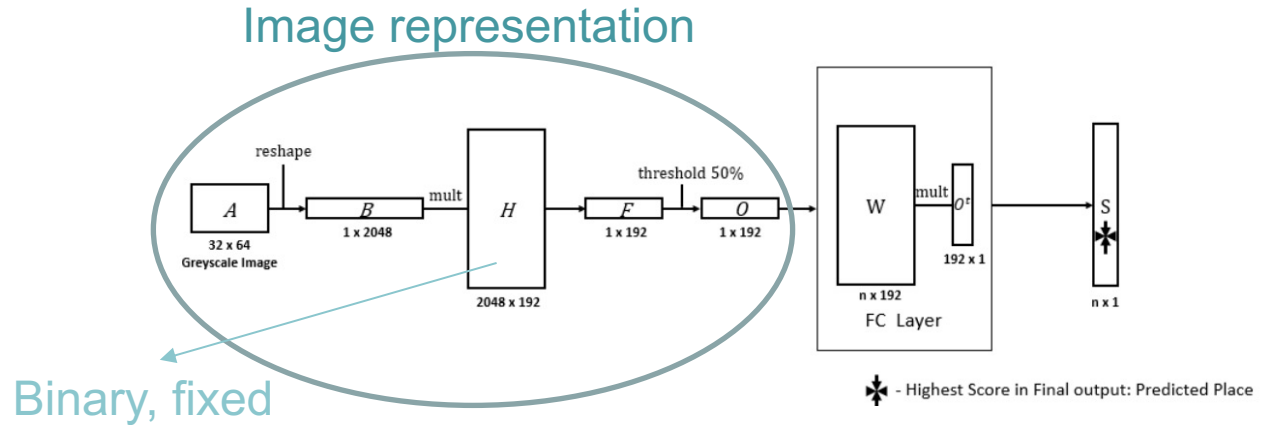
And thus, combining techniques was born

Combining Fly-Inspired Units By Voting

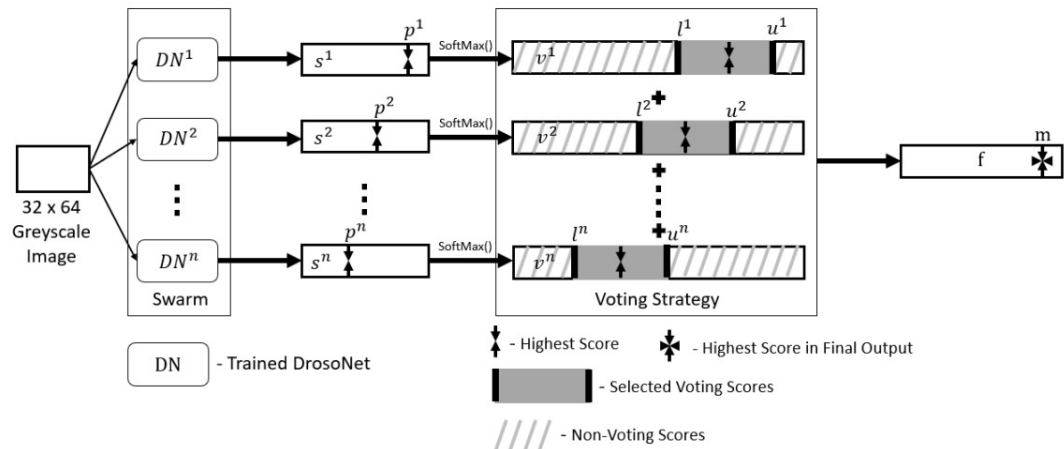
Baseline: Drosonet

Sources of variation:

- Random H matrix
- Random FC inits.

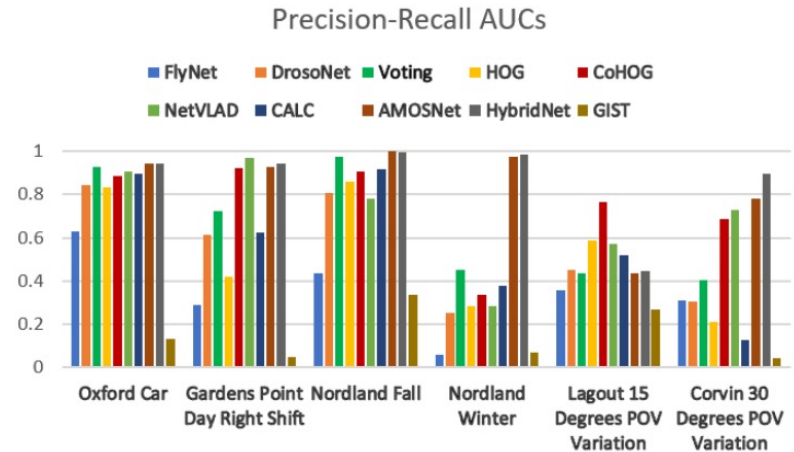


Combination Method:
Voting



VPR Performance

Note: VPR performance is usually evaluated in terms of area-under-the precision recall curve (PR-AUC)



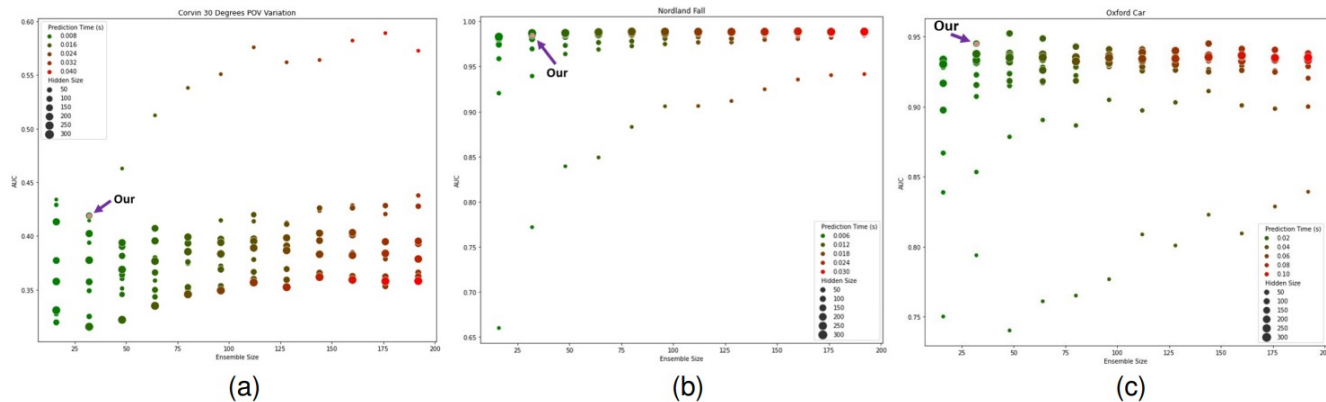
PREDICTION TIMES AND MEMORY USAGE COMPARISON

Model	Prediction time (ms)	FPS	Size (MBs)
HybridNet	1143.92	0.87	61.44
AMOSNet	1138.97	0.88	61.44
CoHOG	3627.18	0.28	123.01
CALC	73.62	13.58	4.26
GIST	225.04	4.44	4.53
HOG	208.71	4.79	142.88
NetVLAD	1435.11	0.70	16.38
FlyNet	1.00	1000	0.26
DrosoNet	1.00	1000	0.19
Voting	18.43	54.27	6.19

Computational Performance

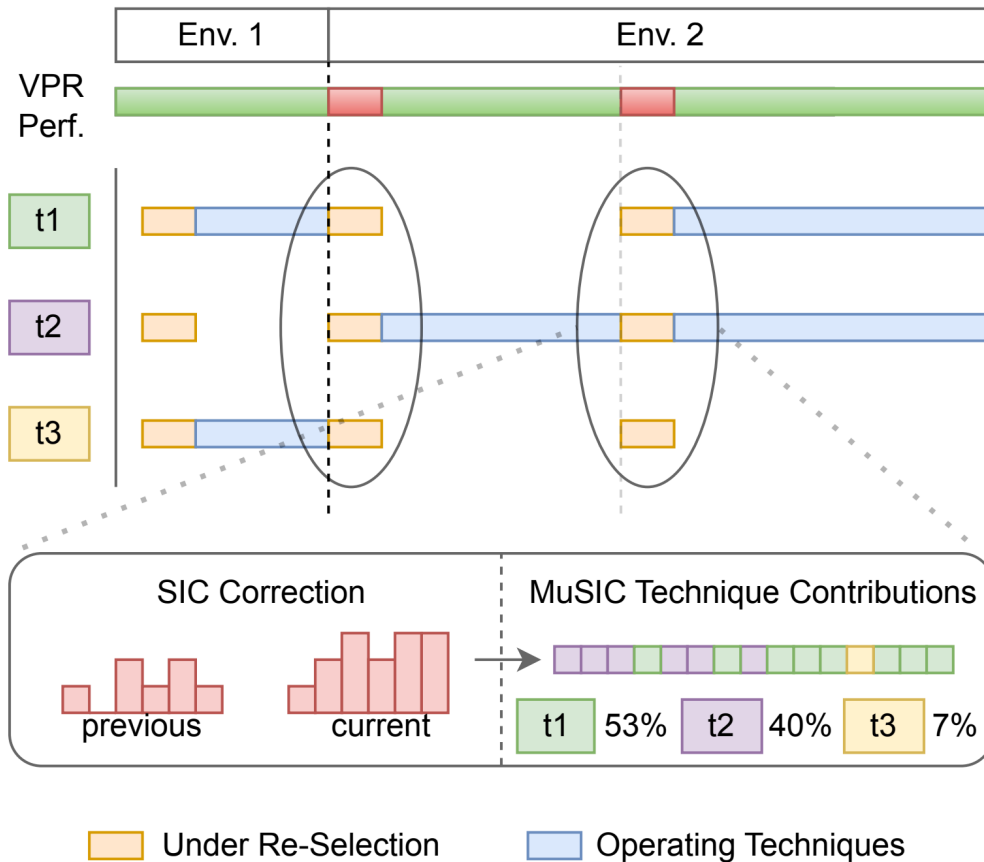
- Not so obvious hyperparameters...

ABLATION STUDIES



- Huge performance disparities depending on random initialization of DrosoneTs
 - Requiring large number of DrosoneTs to guarantee performance (we used 32 baseline models in our work)

A-MUSIC SYSTEM



Self Identification and Correction (SIC)

Multi-SIC (MuSIC)

Adaptive-MuSIC (A-MuSIC)

A-MuSIC Results And Selection Pattern

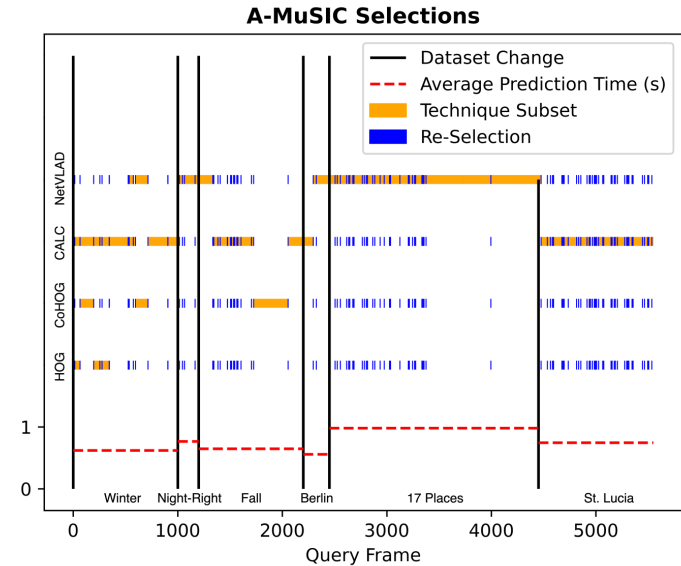
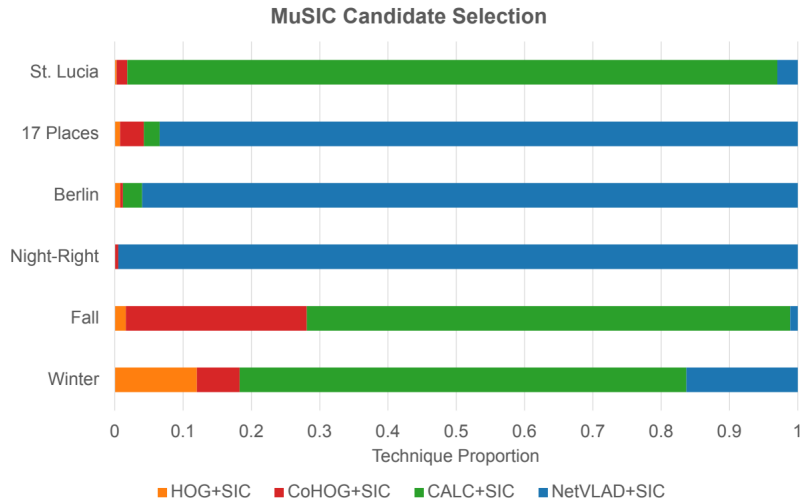
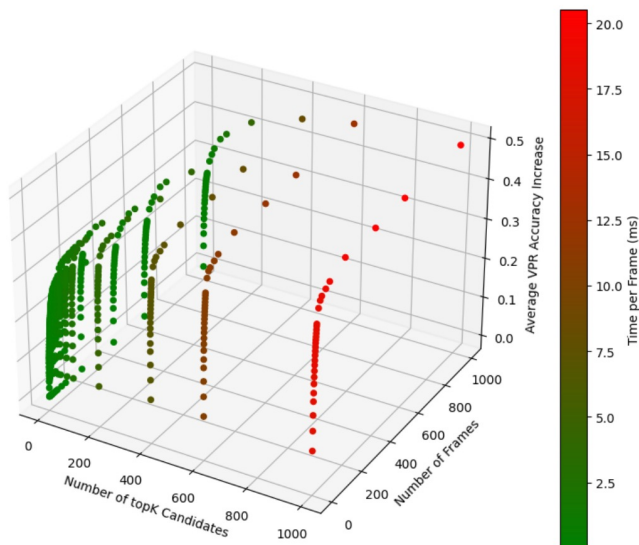


TABLE II: VPR Performance (AUC) and Prediction Time (ms)

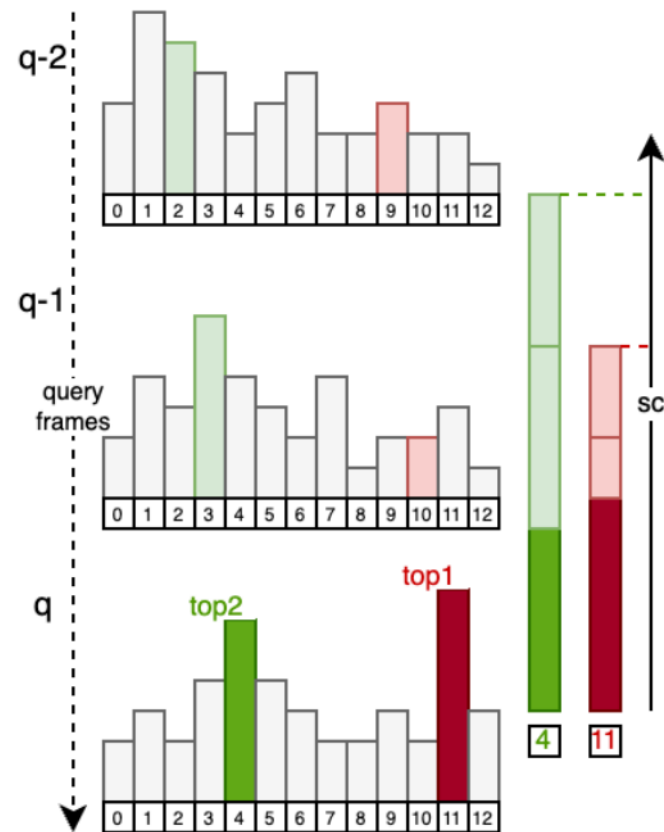
	Winter		Fall		Berlin		Night-Right		17 Places		St. Lucia		Average	
	AUC	ms	AUC	ms	AUC	ms	AUC	ms	AUC	ms	AUC	ms	AUC	ms
HOG	0.29	49	0.84	48	0.03	16	0.03	15	0.34	96	0.56	47	0.35	45
CALC	0.30	168	0.88	168	0.06	157	0.13	161	0.38	170	0.48	165	0.37	165
CoHOG	0.23	795	0.85	785	0.28	225	0.45	185	0.31	1525	0.37	729	0.42	707
NetVLAD	0.28	723	0.68	719	0.81	722	0.54	717	0.48	727	0.35	721	0.52	722
HOG+SIC	0.76	54	0.98	55	0.02	20	0.40	17	0.46	104	0.84	52	0.58	50
CALC+SIC	0.86	172	0.99	175	0.56	163	0.71	163	0.67	177	0.92	170	0.79	170
CoHOG+SIC	0.67	747	0.99	776	0.80	218	0.87	184	0.76	1518	0.84	718	0.82	694
NetVLAD+SIC	0.78	747	0.94	743	0.96	736	0.97	742	0.82	745	0.85	717	0.89	738
MuSIC	0.95	1790	1.00	1748	0.95	1164	0.97	1094	0.86	2544	0.92	1937	0.94	1713
A-MuSIC	0.90	621	0.97	649	0.95	558	0.98	766	0.85	982	0.92	747	0.93	721

A-MuSIC Limitations

- Dependence on sequential imagery
- Still quite a lot of re-selection false positives
- Again, not so obvious hyperparameters



SIC WITH K=2, F=2



- Extend DrosoNet and Voting to achieve better individual performance
 - DrosoNet currently works as a classifier, adapting it to work as a local descriptor could be useful for viewpoint resilience
 - A new fusion/voting/combination schema on this DrosoNet descriptor can be developed for better performance at still a low comp. cost
- Extend A-MuSIC selection decision to take computational cost into account
 - If deciding between two equally performing techniques, the less expensive one should be preferred
 - If deciding between two differently performing techniques, the tradeoff of performance-cost ratio should be a major factor