Apprentissage de modalités auxiliaires pour la localisation basée vision

Enhancing Visual-Based Localization by Learning Appearance of Paired Modalities

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Congrès Reconnaissance des Formes, Image, Apprentissage et Perception 2018

Introduction

Visual Based Localization (**VBL**) aims to recover the pose or position of a visual input query according to a known reference [Piasco et al., 2017].

$\rightarrow$ **?** $\rightarrow$

Visual Based Localization: Indirect methods

VBL can be solved by retrieving the closest geo-referenced candidate in the database.


26.45 04.52


26.45 04.52


27.55 03.99


27.69 03.80


→


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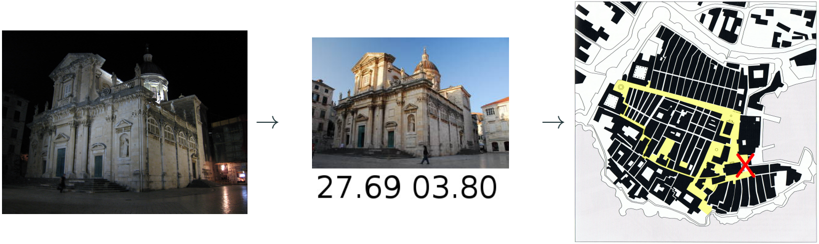
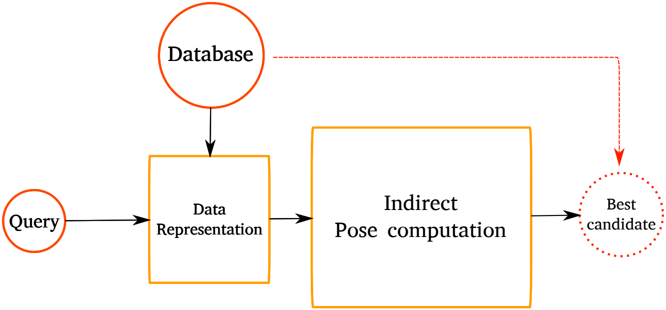


We propose a new data representation for solving indirect VBL.

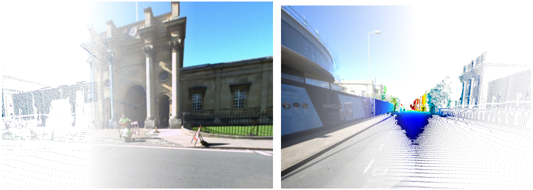


Heterogeneous modalities

Available data

Training data type	Testing data type
RGB + Depth	RGB

Multi-modal training dataset



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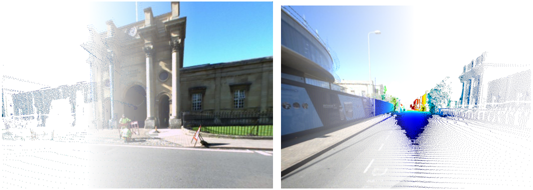
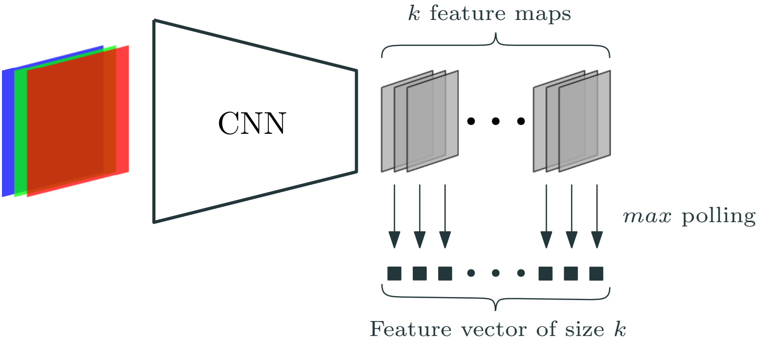


Single modality data at test time

Related work

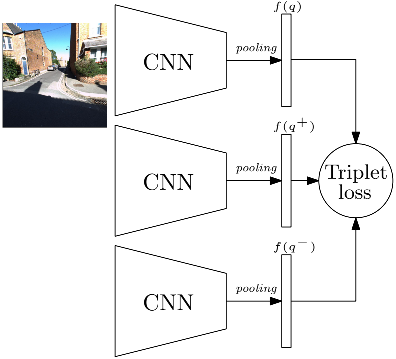
Building a deep image descriptor

Fully connected part of a the network is dropped and pooling is done on the last convolutional response:



More complex aggregation methods exist:
NetVLAD [Arandjelović et al., 2017], RMAC...

Learning a deep image descriptor



$$Loss_{triplet} = max\left(\left\|f(q) - f(q^+)\right\|^2 - \left\|f(q) - f(q^-)\right\|^2 + \lambda, 0\right), \quad (1)$$

$$with \begin{cases} f(x) = \text{descriptor of image } x \\ \lambda = \text{triplet loss margin} \\ q = \text{query image} \\ q^+ = \text{positif example} \\ q^- = \text{negatif example} \end{cases}$$

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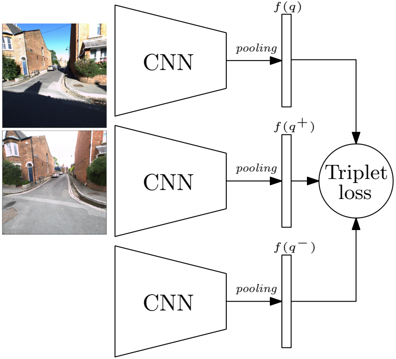

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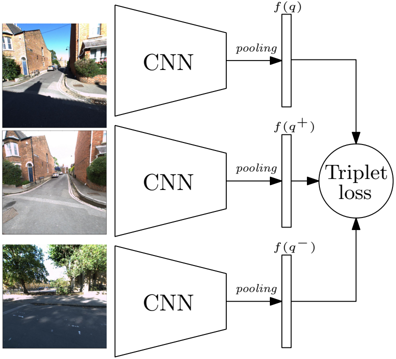

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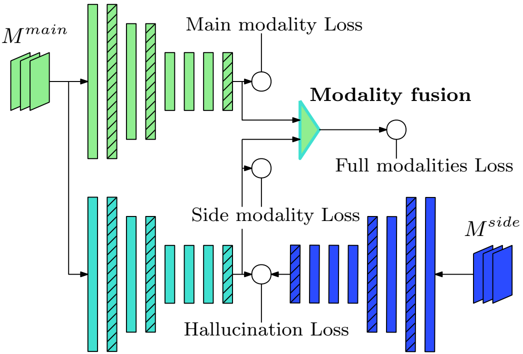

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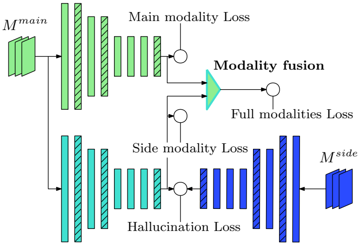
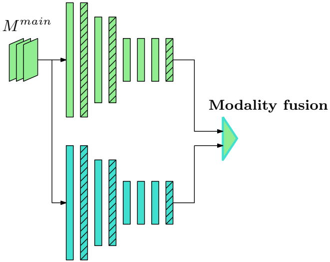




Deployment

Learning side information with modality transfer

Intuition

Current encoder-decoder network architecture currently outperform all other methods for **modality transfer**.

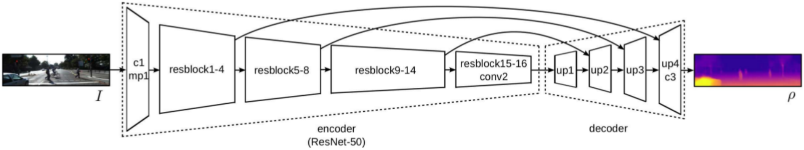
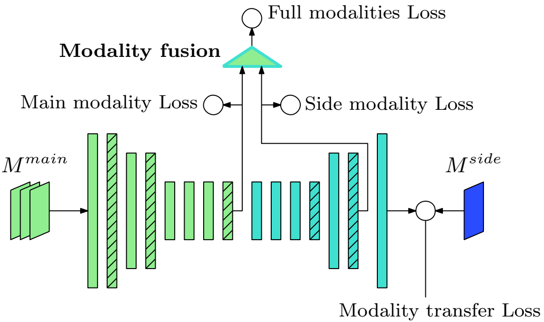


Illustration from [Kuznietsov et al., 2017]

The proposed architecture inspired by encoder-decoder networks:



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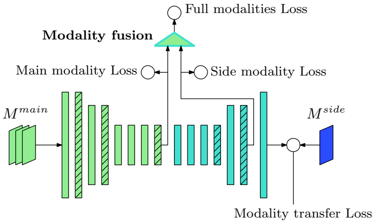

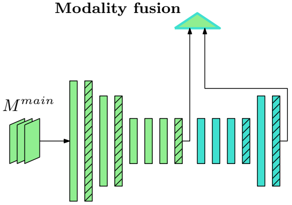

Deployment

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$$Loss_{transfer} = \left\| \widetilde{M}(M^{main}) - M^{side} \right\|_1 , \tag{2}$$

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Final loss:

$$\begin{aligned} Loss = Loss^{main}_{triplet} + Loss^{side}_{triplet} * \sigma_{side} \\ + Loss^{full}_{triplet} * \sigma_{full} + Loss_{transfer} * \sigma_{transfer} . \end{aligned} \quad (3)$$

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Diversification loss:

$$Loss_{div} = max \left(Loss_{triplet}^{full} - Loss_{triplet}^{main} + \lambda_{div} , 0 \right) , \tag{4}$$

where λ_{div} is a scalar value that acts as a margin to ensure $Loss_{triplet}^{full}$ is always smaller than $Loss_{triplet}^{main}$.

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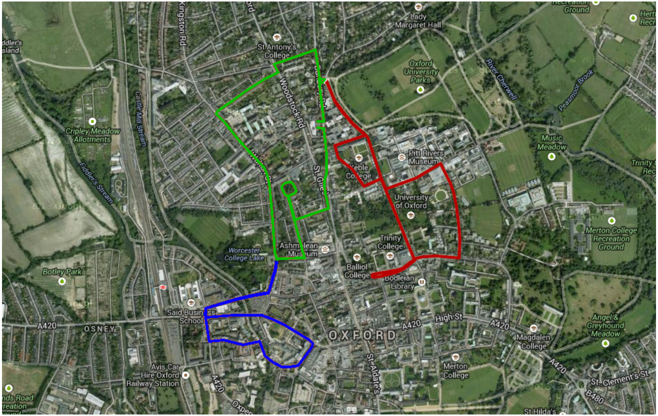
- Method by nature lighter: $29k$ parameters vs. $41k$ parameters for networks built upon Alexnet architecture
- No need to transform modality into 3-channels data

Experiments

Robotcar dataset



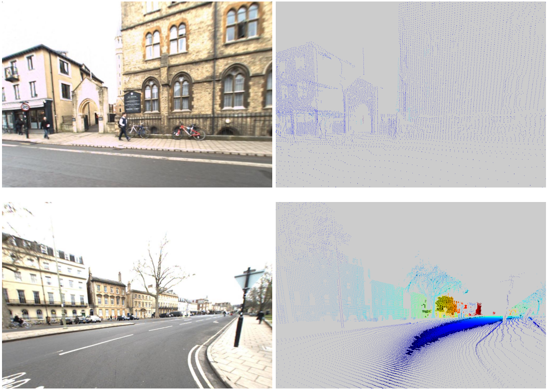
Dataset training (green), validation (blue) and testing (red) areas.

Robotcar dataset

Examples of queries with corresponding dataset candidates of the testing set.

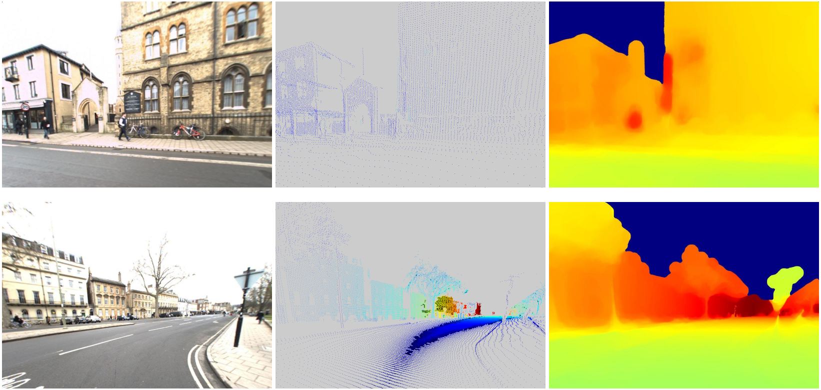
Building dense modality map

Image **Points cloud**



We use the algorithm proposed in [Bevilacqua et al., 2017] to create a dense modality map from an image and the associated point cloud.

Image | Points cloud | Dense depth map



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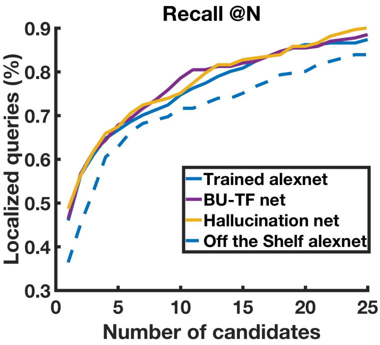
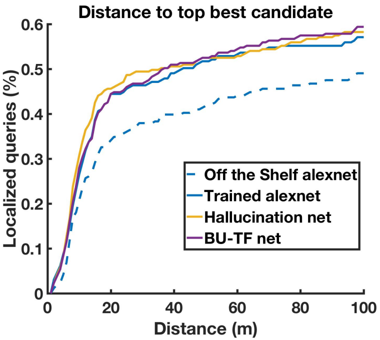
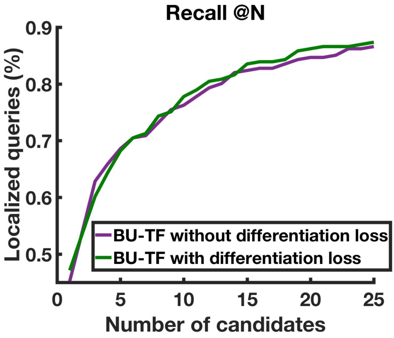
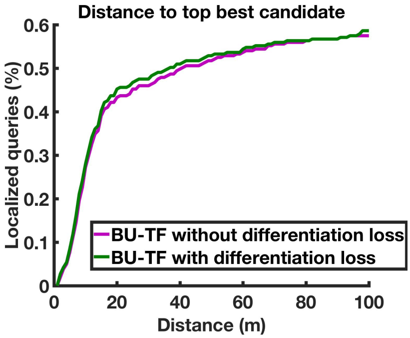




Off-the-shelf: network only trained on ImageNet, no fine-tuning for this specific task and on these specific data.


Recall @N
Localized queries (%)
0.9
0.8
0.7
0.6
0.5
0
5
10
15
20
25
Number of candidates
BU-TF without differentiation loss
BU-TF with differentiation loss

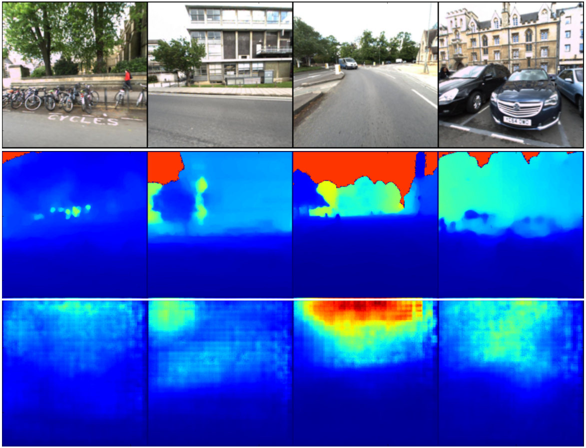

Distance to top best candidate
Localized queries (%)
0.6
0.5
0.4
0.3
0.2
0.1
0
0
20
40
60
80
100
Distance (m)
BU-TF without differentiation loss
BU-TF with differentiation loss

Results - Visual inspection

Main modality

Side modality

Reconstructed side modality



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Future work – The presented method has to be tested:

- on other modalities
- with other aggregation scheme
- on other visual localisation tasks (*e.g.* pose regression)

Thanks for your attention

Question time

References I

Arandjelović, R., Gronat, P., Torii, A., Pajdla, T., and Sivic, J. (2017).
NetVLAD: CNN architecture for weakly supervised place recognition.
IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), pages 5297–5307.

Bevilacqua, M., Aujol, J. F., Biasutti, P., Brédif, M., and Bugeau, A. (2017).
Joint inpainting of depth and reflectance with visibility estimation.
ISPRS Journal of Photogrammetry and Remote Sensing, 125:16–32.

Hoffman, J., Gupta, S., and Darrell, T. (2016).
Learning with Side Information through Modality Hallucination.
In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 826–834.

References II

Kuznietsov, Y., Stückler, J., and Leibe, B. (2017).
Semi-Supervised Deep Learning for Monocular Depth Map Prediction.
In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Piasco, N., Sidibé, D., Demonceaux, C., and Gouet-Brunet, V. (2017).
A survey on Visual-Based Localization: On the benefit of heterogeneous data.
Pattern Recognition, 74:90–109.