Apprentissage de modalités auxiliaires pour la localisation basée vision

Enhancing Visual-Based Localization by Learning Appearance of Paired Modalities

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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].

Graph illustration VBL: Query $\rightarrow$? $\rightarrow$ Map

Visual Based Localization: Indirect methods

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

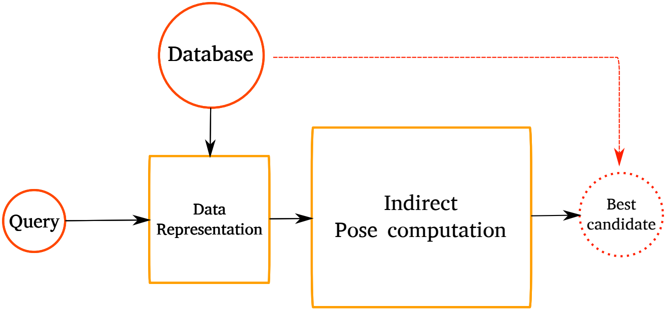
Graph illustration VBL: Query $\rightarrow$ Geo-taged images $\rightarrow$ Map

Visual Based Localization: Indirect methods

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

Graph illustration VBL: Query $\rightarrow$ Closest Geo-taged image $\rightarrow$ Map location

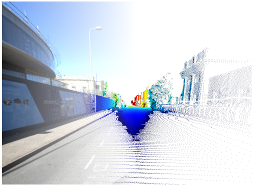
We propose a new data representation for solving indirect VBL.



Available data

Training data type	Testing data type
RGB + Depth	RGB

Multi-modal training dataset



Heterogeneous modalities

Available data

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RGB + Depth	**RGB**

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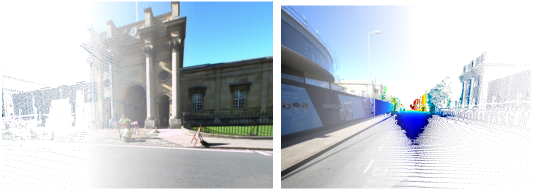
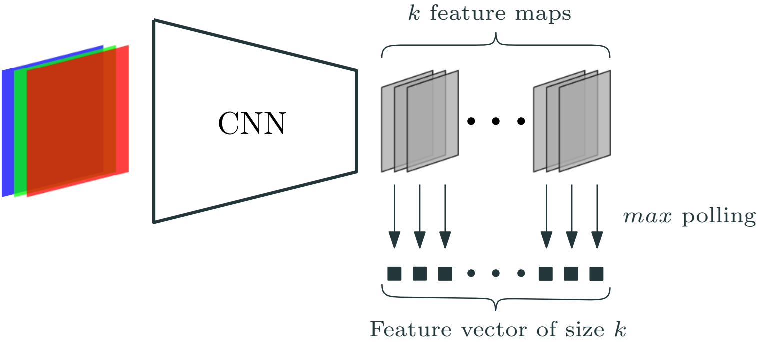


Single modality data at test time

Related work

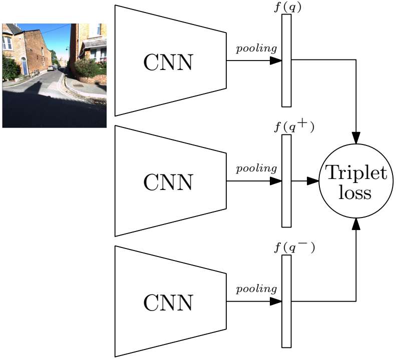
Building a deep image descriptor

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



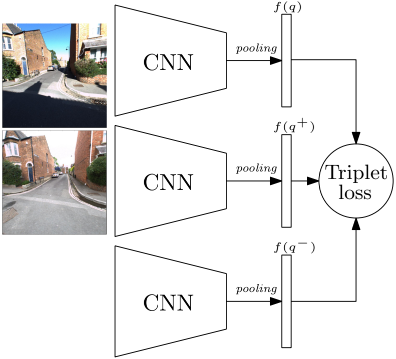
More complex aggregation methods exist:
NetVLAD [Arandjelović et al., 2017], RMAC...

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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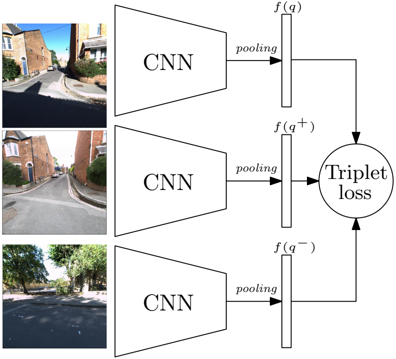

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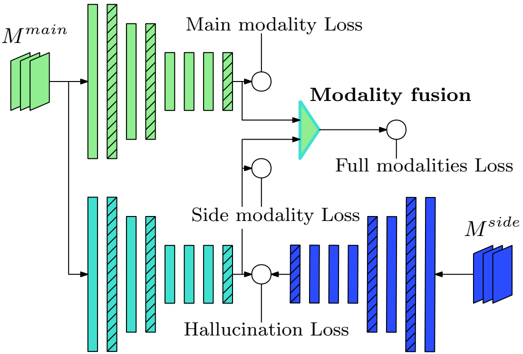

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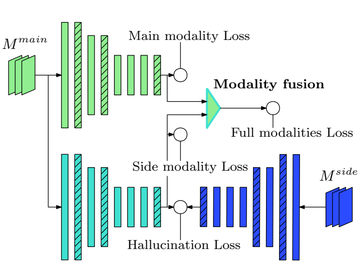
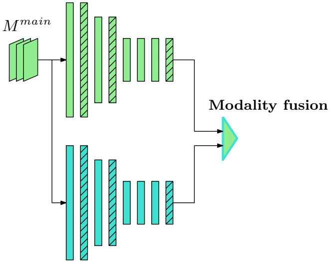




Deployment

Learning side information with modality transfer

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

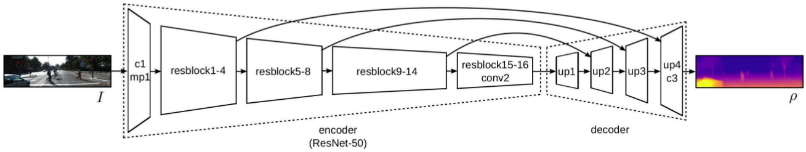
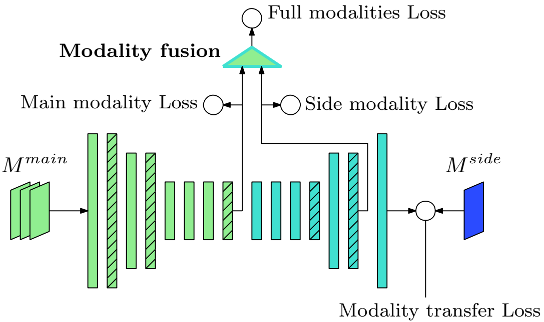


Illustration from [Kuznietsov et al., 2017]

The proposed architecture inspired by encoder-decoder networks:



Training

Proposed architecture

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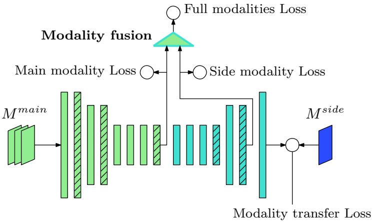

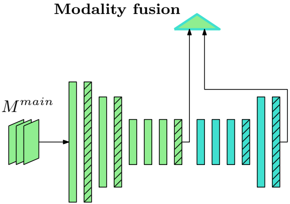

Deployment

Optimization

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

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Final loss:

$$\begin{aligned} Loss = {} & Loss_{triplet}^{main} + Loss_{triplet}^{side} * \sigma_{side} \\ & + Loss_{triplet}^{full} * \sigma_{full} + Loss_{transfer} * \sigma_{transfer} . \end{aligned} \tag{3}$$

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Diversification loss:

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

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

Advantages over hallucination

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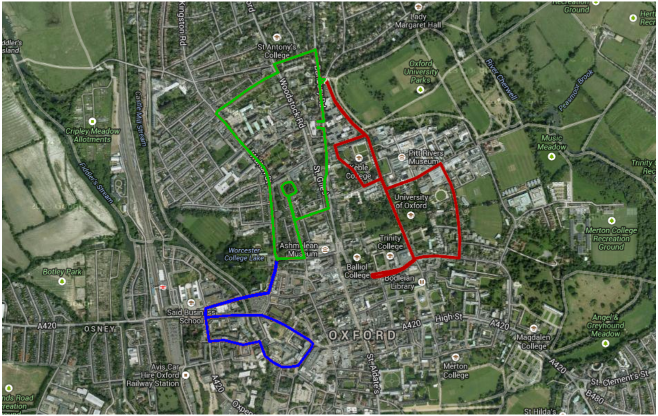
- No need of pretraining on side modality
- Method by nature lighter: $29k$ parameters vs. $41k$ parameters for networks built upon Alexnet architecture
- No need to transform modality into 3-channels data

Experiments



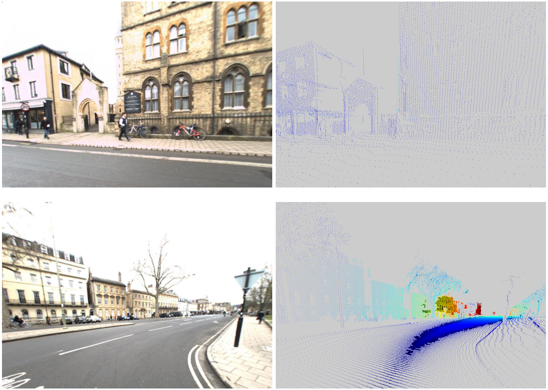
Dataset training (green), validation (blue) and testing (red) areas.

Robotcar dataset

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

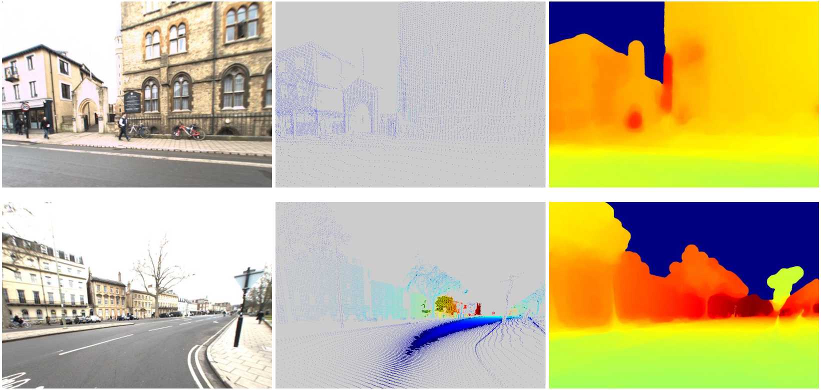
Building dense modality map

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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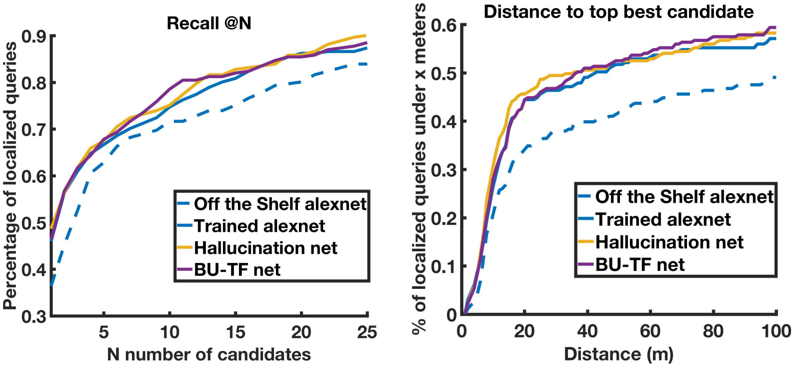
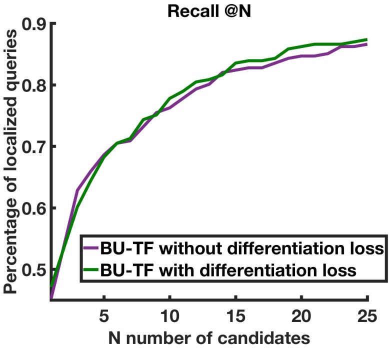
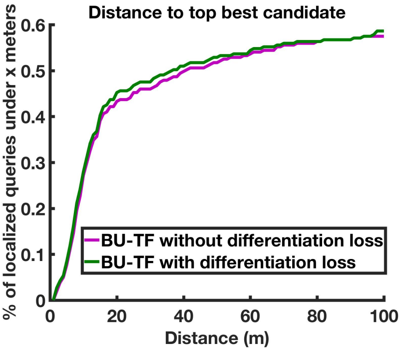
Results



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

Results - Diversification loss

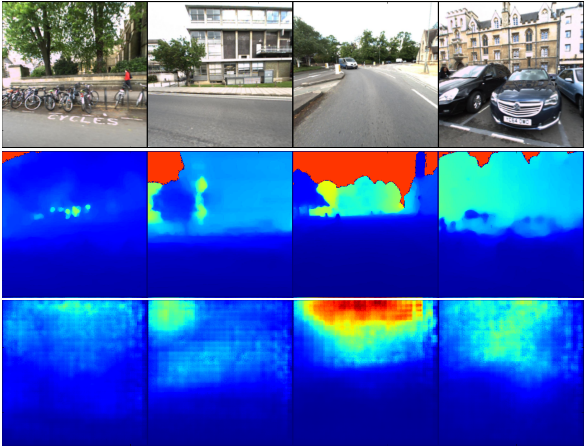




Main modality

Side modality

Reconstructed side modality



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Future work – The presented method has to be tested:

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

Thanks for your attention

Question time

References I

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