



# Apprentissage de modalités auxiliaires pour la localisation basée vision

Enhancing Visual-Based Localization by Learning Appearance of Paired Modalities

---

Nathan Piasco

26/06/2018

Congrès Reconnaissance des Formes, Image, Apprentissage et Perception 2018

Introduction

Related work

Our proposal: Learning side information with modality transfer

Experiments

Conclusion

## **Introduction**

---

# Visual Based Localization

Visual Based Localization (**VBL**) aims to recover the pose or position of a visual input query according to a known visual reference.

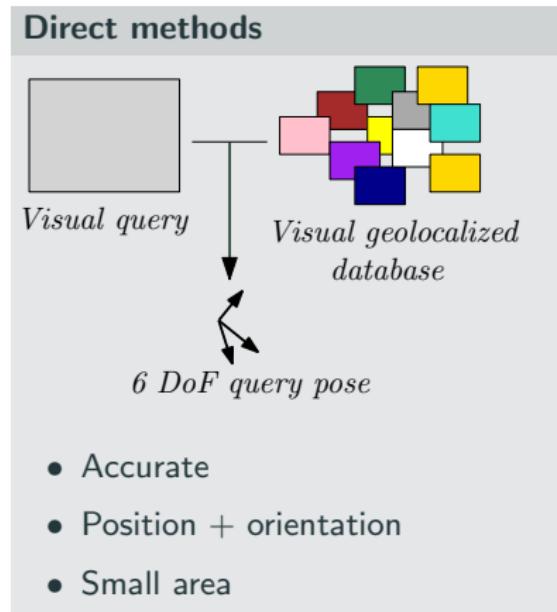


→ ? →



# Direct vs Indirect methods

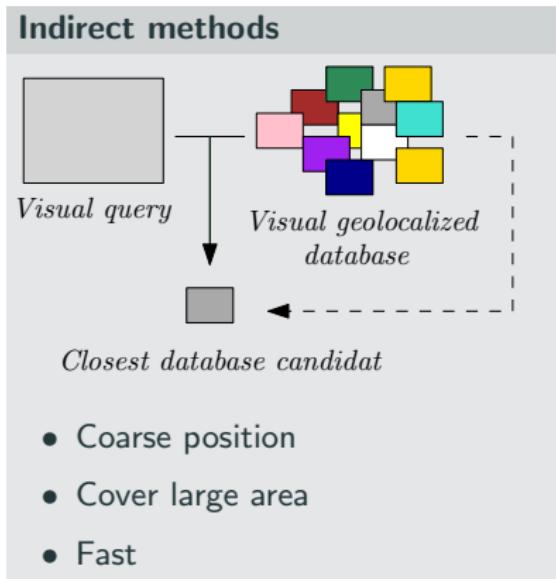
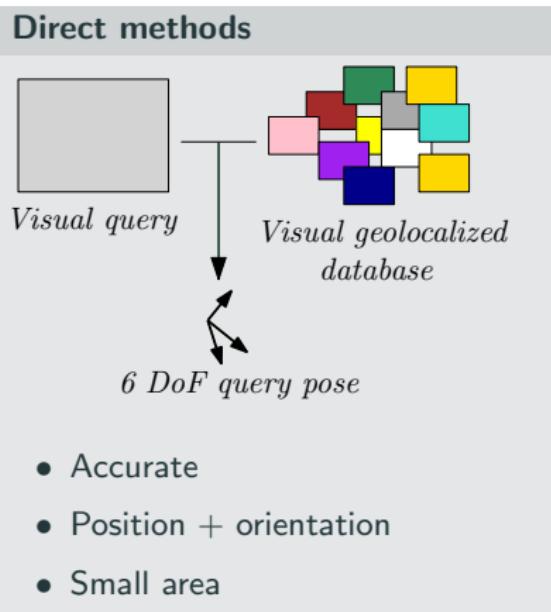
Visual Based Localization (**VBL**) methods can be divided in two main categories [Piasco et al., 2017]:



- Accurate
- Position + orientation
- Small area

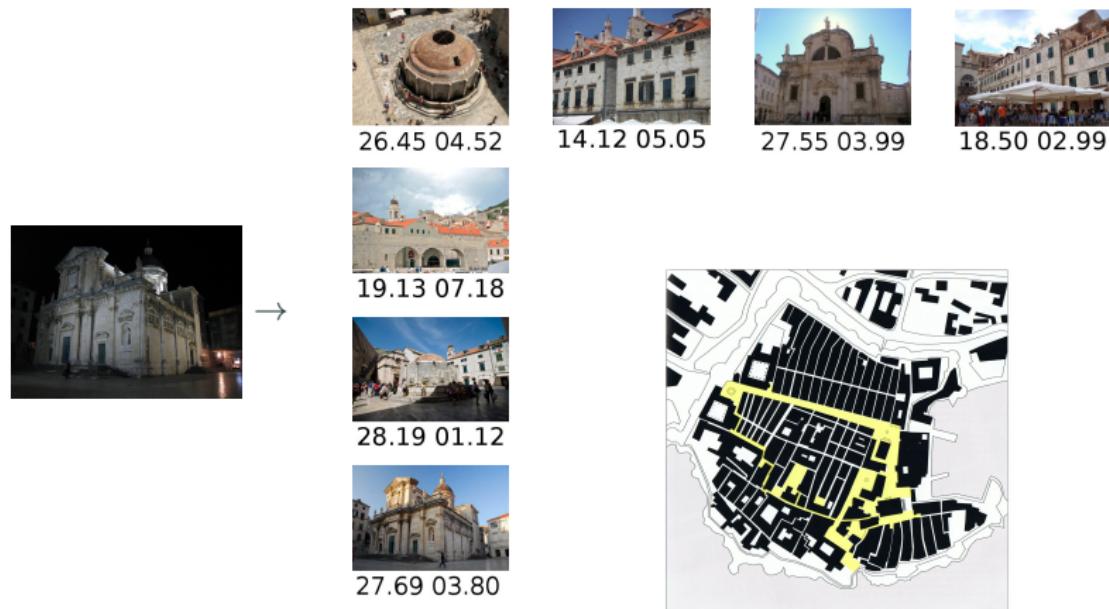
# Direct vs Indirect methods

Visual Based Localization (**VBL**) methods can be divided in two main categories [Piasco et al., 2017]:



# Visual Based Localization: Indirect methods

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



# Visual Based Localization: Indirect methods

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



27.69 03.80

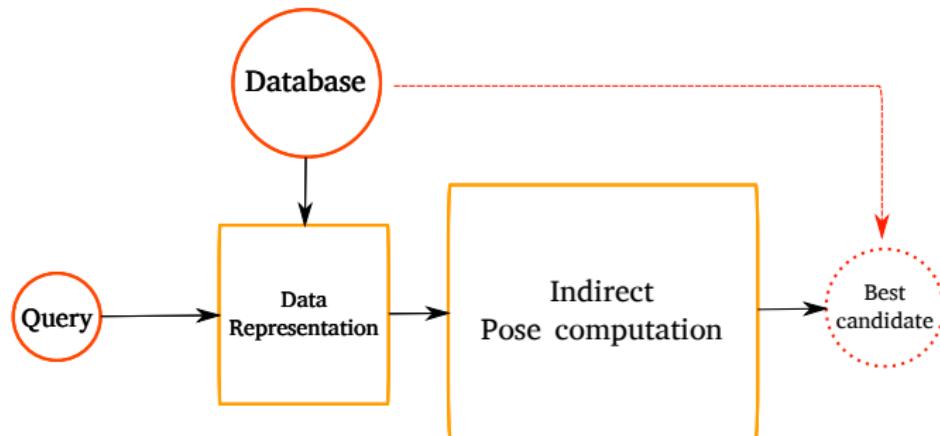


Introduction



# Indirect methods: Pipeline

We propose a new data representation for solving indirect VBL.



# Various modalities

In this work, we tackle the problem of VBL with **not only** images.

## Modalities that could be used

- Image (main modality)



INSTITUT NATIONAL  
DE L'INFORMATIQUE  
DES TELECOMS  
ET DES SYSTEMES

## Introduction



UNIVERSITE  
BOURGOGNE FRANCHE-COMTE

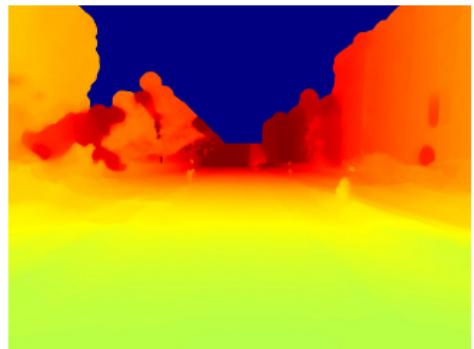


# Various modalities

In this work, we tackle the problem of VBL with **not only** images.

## Modalities that could be used

- **Image** (main modality)
- Depth map



## Introduction

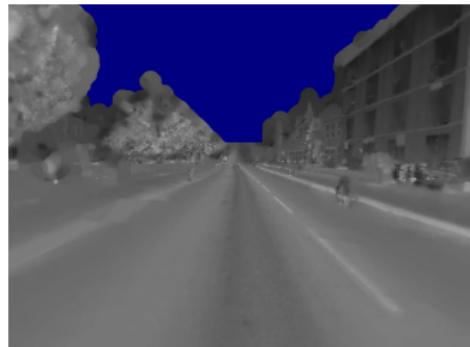


# Various modalities

In this work, we tackle the problem of VBL with **not only** images.

## Modalities that could be used

- **Image** (main modality)
- Depth map
- Reflectance



INSTITUT NATIONAL  
DE L'INFORMATIQUE  
DES TELECOMS  
ET DES SYSTEMES

## Introduction



UNIVERSITE  
BOURGOGNE FRANCHE-COMTE



# Various modalities

In this work, we tackle the problem of VBL with **not only** images.

## Modalities that could be used

- **Image** (main modality)
- Depth map
- Reflectance
- Semantic information
- ...



INSTITUT NATIONAL  
DE L'INFORMATIQUE  
DES TELECOMS  
ET DES SYSTEMES

## Introduction



# Heterogeneous modalities

## Available data

Training data type	Testing data type
RGB + Depth	RGB

Multi-modal training dataset

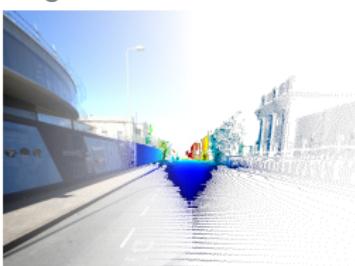


# Heterogeneous modalities

## Available data

Training data type	Testing data type
RGB + Depth	RGB

Multi-modal training dataset



Single modality data at test



## Introduction

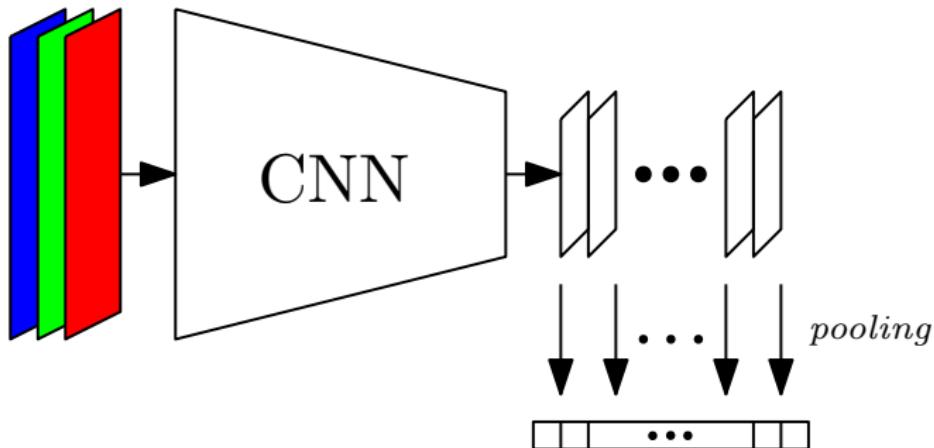


## **Related work**

---

## Building a deep image descriptor

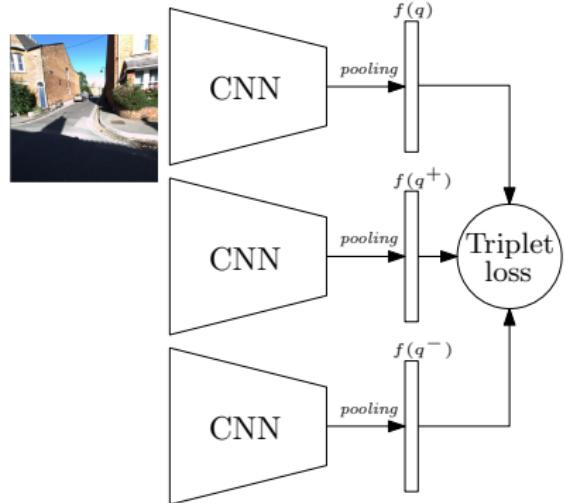
Fully connected part of the network is dropped and pooling is done on the last convolutional response:



More complex aggregation methods exist:

NetVLAD [Arandjelović et al., 2017], RMAC [Radenović et al., 2016]...

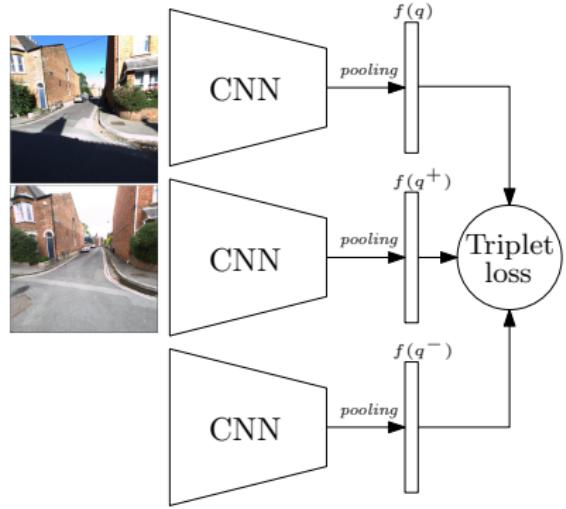
# Learning a deep image descriptor



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

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

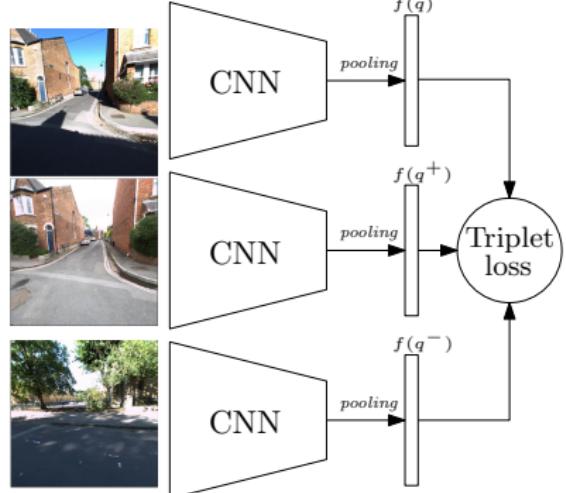
# Learning a deep image descriptor



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

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

# Learning a deep image descriptor

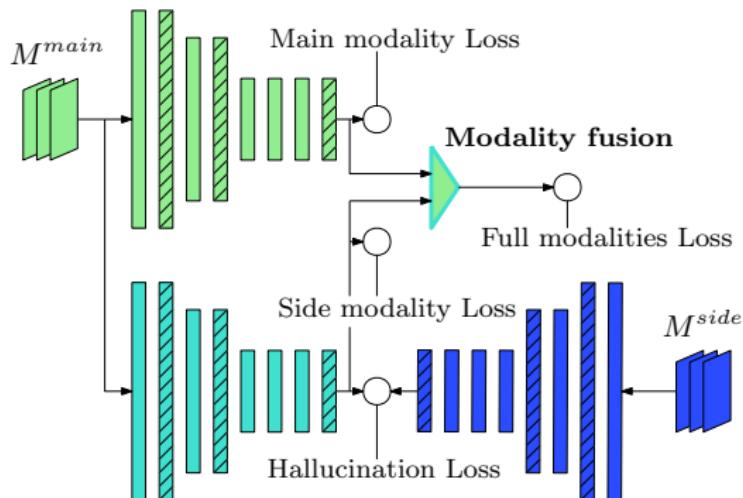


$$Loss_{triplet} = \max \left( \|f(q) - f(q^+)\|^2 - \|f(q) - f(q^-)\|^2 + \lambda, 0 \right), \quad (1)$$

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

# Learning with side modality

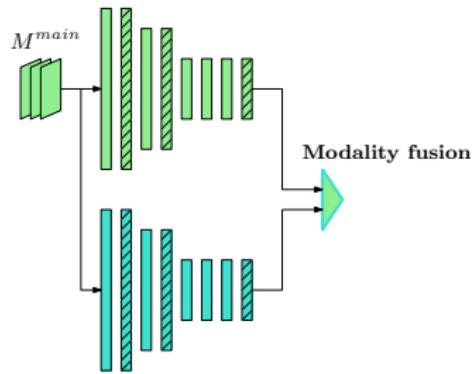
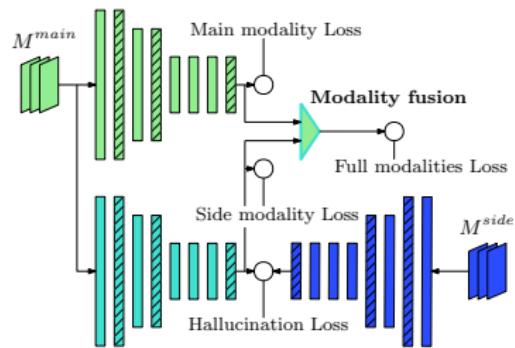
Hallucination architecture from [Hoffman et al., 2016] for objects classification, never applied to image description and VBL.



Related work

# Learning with side modality

Hallucination architecture from [Hoffman et al., 2016] for objects classification, never applied to image description and VBL.



Deployment

## **Our proposal: Learning side information with modality transfer**

---

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

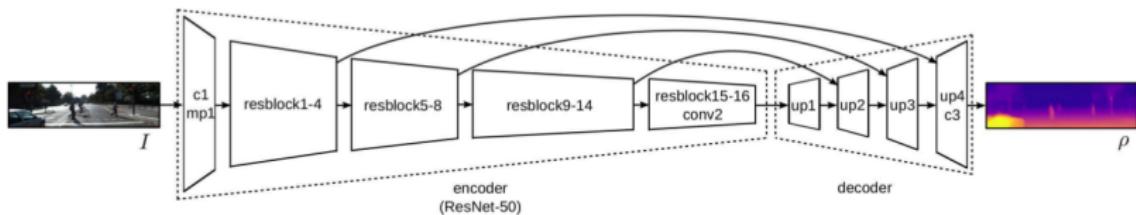
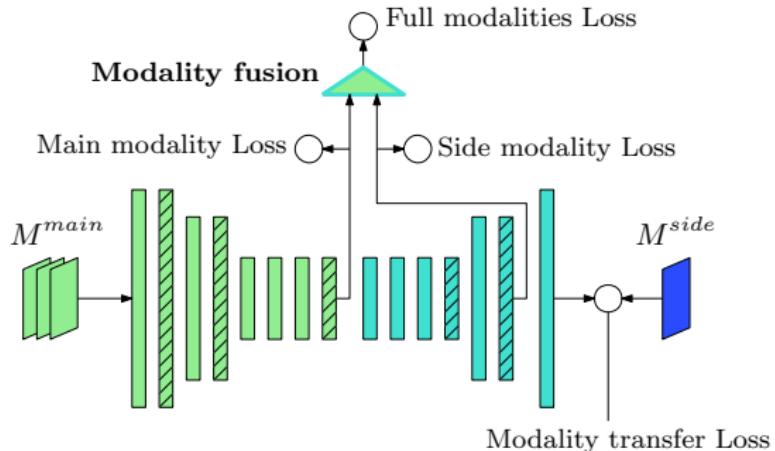


Illustration from [Kuznetsov et al., 2017]

# Proposed architecture

The proposed architecture is inspired by encoder-decoder networks:



Training

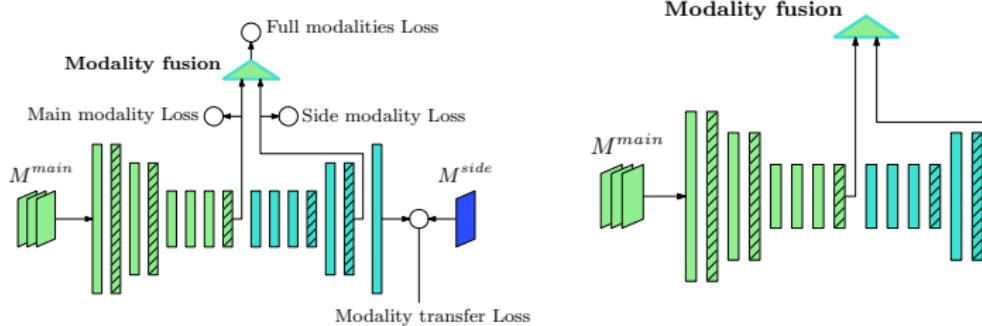


Our proposal: Learning side information with modality transfer



# Proposed architecture

The proposed architecture is inspired by encoder-decoder networks:



Deployment

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

where  $\tilde{M}(x)$  denotes the output of the decoder part of the network regarding input  $x$ .

# Optimization

$$\text{Loss}_{\text{transfer}} = \left\| \tilde{M}(M^{\text{main}}) - M^{\text{side}} \right\|_1, \quad (2)$$

where  $\tilde{M}(x)$  denotes the output of the decoder part of the network regarding input  $x$ .

Final loss:

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

# Optimization

$$\text{Loss}_{\text{transfer}} = \left\| \tilde{M}(M^{\text{main}}) - M^{\text{side}} \right\|_1, \quad (2)$$

where  $\tilde{M}(x)$  denotes the output of the decoder part of the network regarding input  $x$ .

Final loss:

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

Diversification loss:

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

where  $\lambda_{\text{div}}$  is a scalar value that acts as a margin to ensure  $\text{Loss}_{\text{triplet}}^{\text{full}}$  is always smaller than  $\text{Loss}_{\text{triplet}}^{\text{main}}$ .

# Advantages over hallucination

Advantages of our bottom-up transfer approach (**BU-TF**) over hallucination network are threefold:

- No need of pretraining on side modality



INSTITUT NATIONAL  
DE L'INFORMATION  
GÉOGRAPHIQUE  
ET forestière

Our proposal: Learning side information with modality transfer



# Advantages over hallucination

Advantages of our bottom-up transfer approach (**BU-TF**) over hallucination network are threefold:

- No need of pretraining on side modality
- Method by nature lighter: 29k parameters vs. 41k parameters for networks built upon Alexnet architecture



INSTITUT NATIONAL  
DE L'INFORMATION  
GÉOGRAPHIQUE  
ET forestière

Our proposal: Learning side information with modality transfer



# Advantages over hallucination

Advantages of our bottom-up transfer approach (**BU-TF**) over hallucination network are threefold:

- 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



INSTITUT NATIONAL  
DE L'INFORMATION  
GÉOGRAPHIQUE  
ET forestière

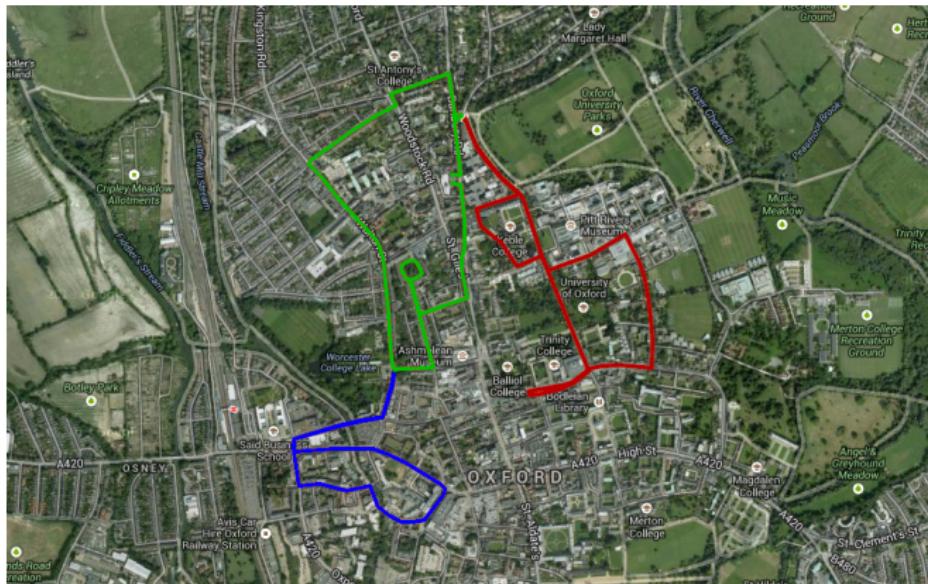
Our proposal: Learning side information with modality transfer



## Experiments

---

# Robotcar dataset



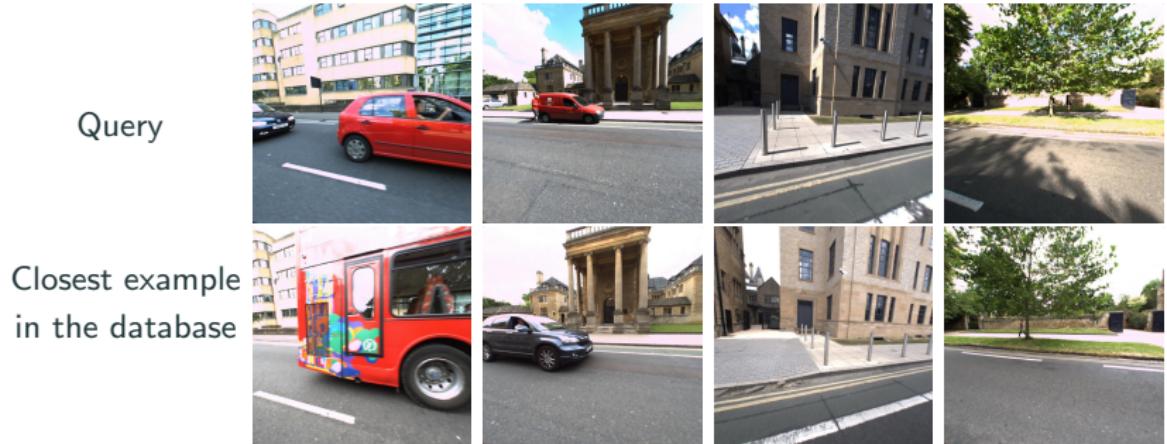
Dataset training (green), validation (blue) and testing (red) areas.



Experiments



# Robotcar dataset



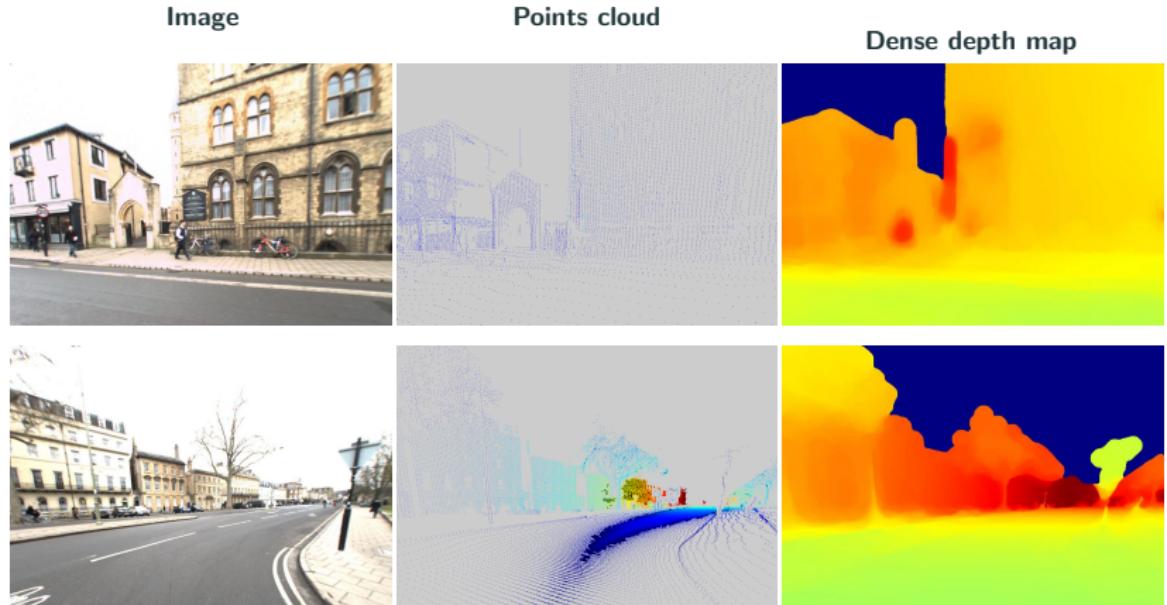
Examples of queries with corresponding dataset candidates of the testing set.

# Building dense modality map



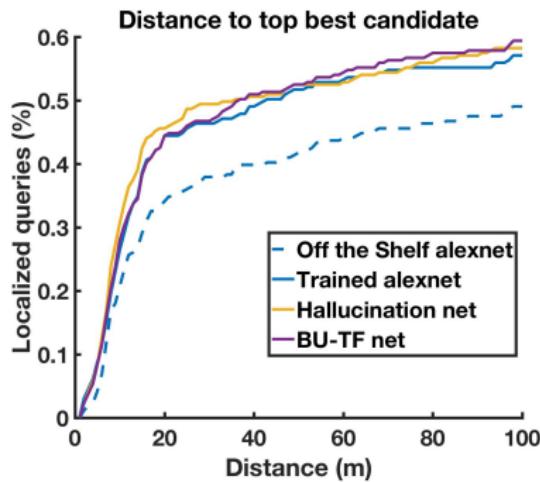
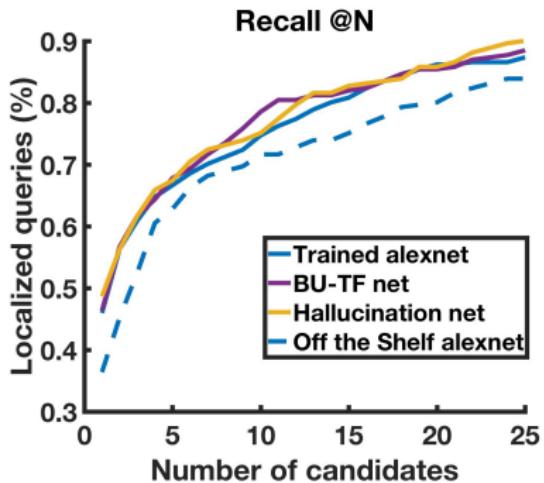
We use the algorithm proposed in [Bevilacqua et al., 2017] to create a dense modality map from an image and the associated point cloud.

# Building dense modality map



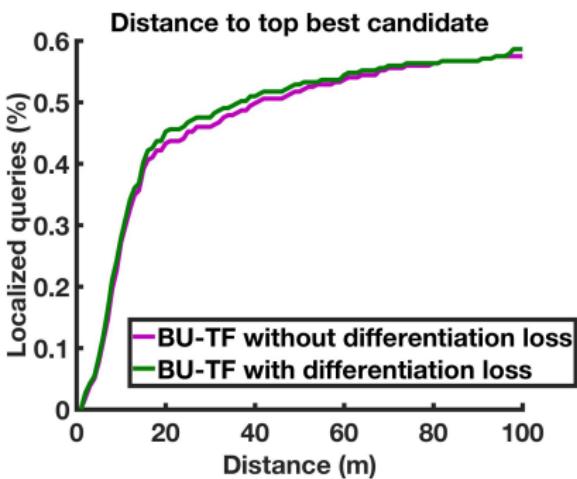
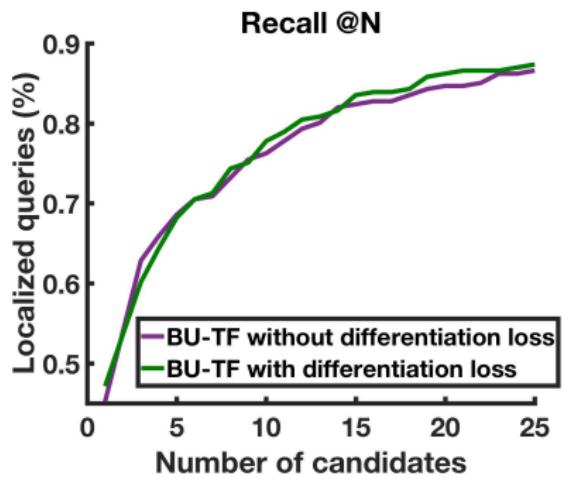
We use the algorithm proposed in [Bevilacqua et al., 2017] to create a dense modality map from an image and the associated point cloud.

# Results



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

## Results - Diversification loss

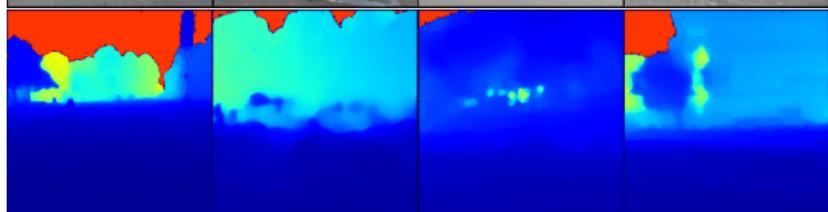


## Results - Visual inspection

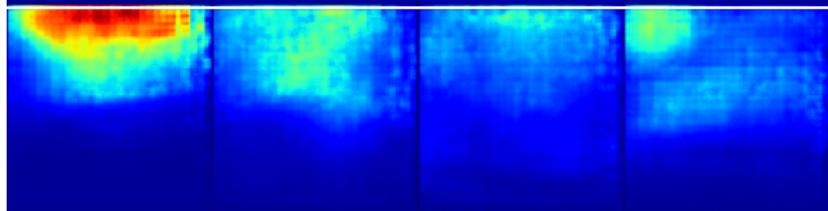
Main modality



Ground truth  
side modality



Reconstructed  
side modality



Experiments



## Results - Conclusion

Comparison with state of the art method:

	Improvement over images-only method	Size	Training steps
Hallucination [Hoffman et al., 2016]			
BU-TF (Our proposal)			

## Results - Conclusion

Comparison with state of the art method:

	Improvement over images-only method	Size	Training steps
Hallucination [Hoffman et al., 2016]	Yes		
BU-TF (Our proposal)	Yes		

## Results - Conclusion

Comparison with state of the art method:

	Improvement over images-only method	Size	Training steps
Hallucination [Hoffman et al., 2016]	Yes	2x	
BU-TF (Our proposal)	Yes	1.4x	

Experiments



## Results - Conclusion

Comparison with state of the art method:

	Improvement over images-only method	Size	Training steps
Hallucination [Hoffman et al., 2016]	Yes	2x	3 steps
BU-TF (Our proposal)	Yes	1.4x	2 steps

## Conclusion

---

# Conclusion

A new method for learning a global image descriptor with side modality has been presented. BU-TF is more efficient than hallucination as it needs less training time and has less parameters while producing comparable results.

# Conclusion

A new method for learning a global image descriptor with side modality has been presented. BU-TF is more efficient than hallucination as it needs less training time and has less parameters while producing comparable results.

*Future work* – The presented method has to be tested:

- on other modalities

# Conclusion

A new method for learning a global image descriptor with side modality has been presented. BU-TF is more efficient than hallucination as it needs less training time and has less parameters while producing comparable results.

*Future work* – The presented method has to be tested:

- on other modalities
- with other aggregation scheme

# Conclusion

A new method for learning a global image descriptor with side modality has been presented. BU-TF is more efficient than hallucination as it needs less training time and has less parameters while producing comparable results.

*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

-  Kuznetsov, 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.
-  Radenović, F., Tolias, G., and Chum, O. (2016).  
**CNN Image Retrieval Learns from BoW: Unsupervised Fine-Tuning with Hard Examples.**  
In *Proceedings of the IEEE European Conference on Computer Vision (ECCV)*, volume 9905, pages 3–20.