CVSSP Centre for Vision, Speech and Signal Processing

Localisation via Deep Imagination: learn the features not the maps

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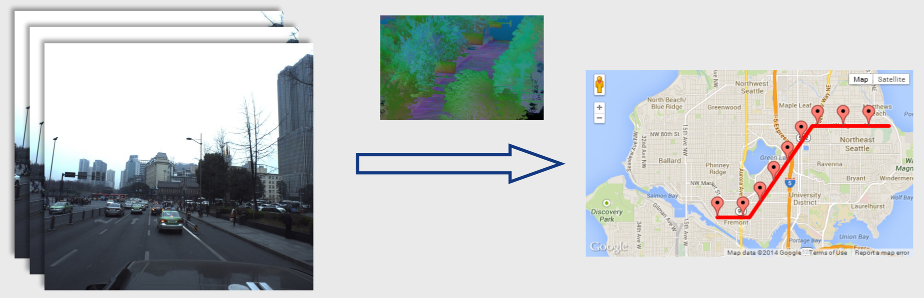
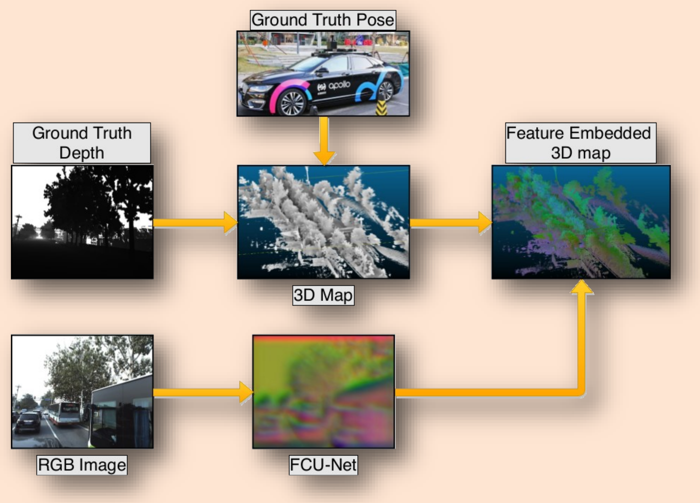
1 - Abstract

- **Localisation** is fundamental to interacting with the world.
- Our work aims to perform **on-the-fly monocular localisation** using a prebuilt 3D map of the world.
- We propose a novel approach where an agent is able to model **new environments** after a **single visitation** by creating a **feature embedded 3D map**.
- The system uses the built map to **"imagine"** the scene's appearance from **novel, unseen poses**. These are used to estimate view likelihood and propagate the particles in a **Deep Imagination** localiser.

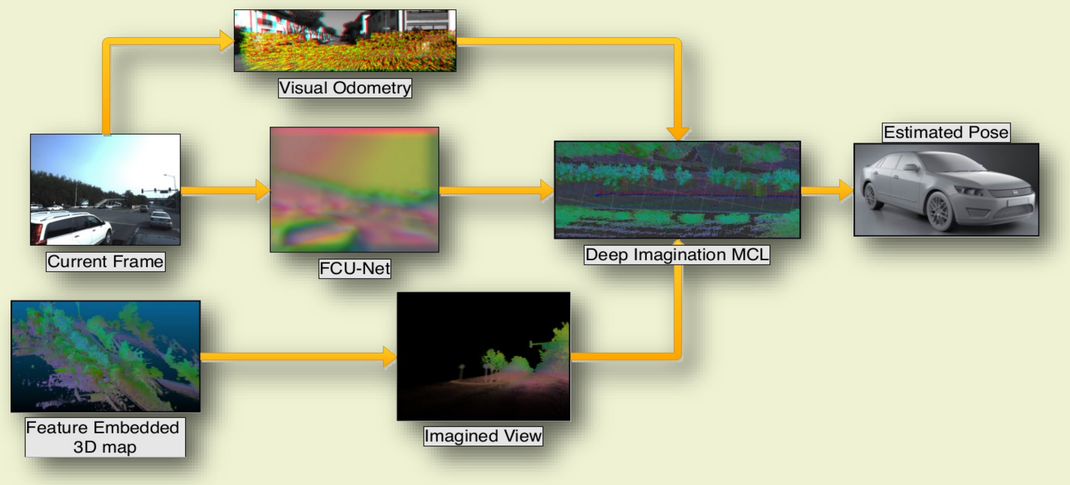


2 - Overview - Map building



- **Dense feature extraction** - Siamese **FCU-Net** pre-trained to produce **appearance invariant** descriptors.
- **Feature embedded 3D map** - **Backproject** FCU-Net **feature maps** into 3D space.

3 - Overview - Deployment



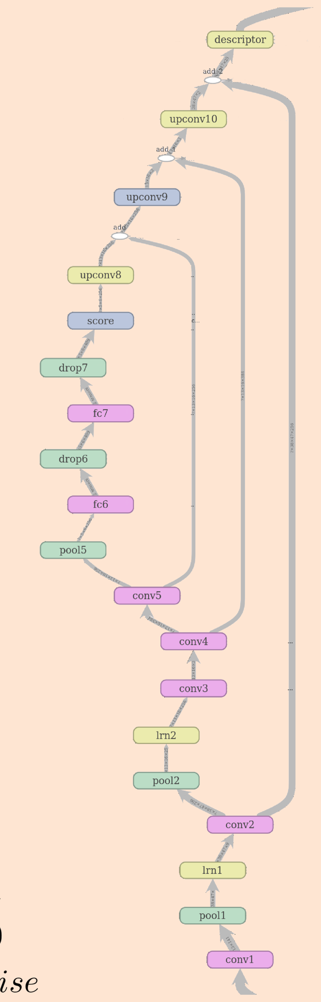
- **Deep Imagination localiser** - **VMCL**; **Project** feature embedded **map** to particle **pose hypothesis** to **"imagine"** the appearance and calculate view likelihood.
- **Visual odometry** - Particle filter **motion model**.

4 - FCU-Net

- **Dense** feature extractor
- **Fully convolutional** encoder-decoder
  - No size restrictions
- **Skip connections**
  - Combine low level **spatial** and high level **semantic features**

- Mapping $U : \mathbb{N}^3 \rightarrow \mathbb{R}^n$
- Training
  - **Siamese** network
  - **Pre-trained** on Kitti dataset
  - Novel **pixel-wise** contrastive loss:

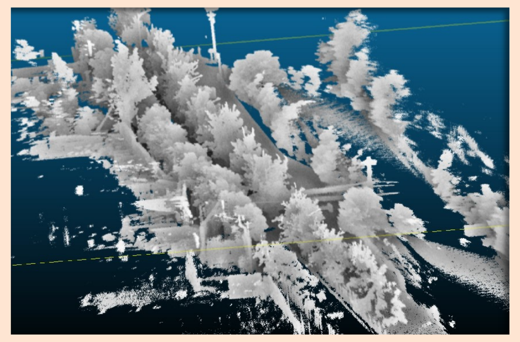
$$l(y, \boldsymbol{p}_1, \boldsymbol{p}_2) = \begin{cases} \frac{1}{2}(d)^2 & \text{if } y = 1 \\ \frac{1}{2}\{\max(0, m - d)\}^2 & \text{if } y = 0 \\ 0 & otherwise \end{cases}$$



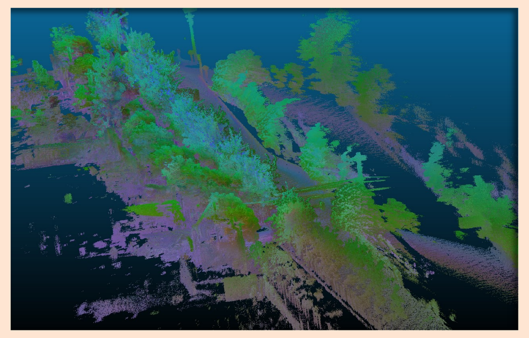
FCU-Net Architecture

5 - Feature embedded 3D map

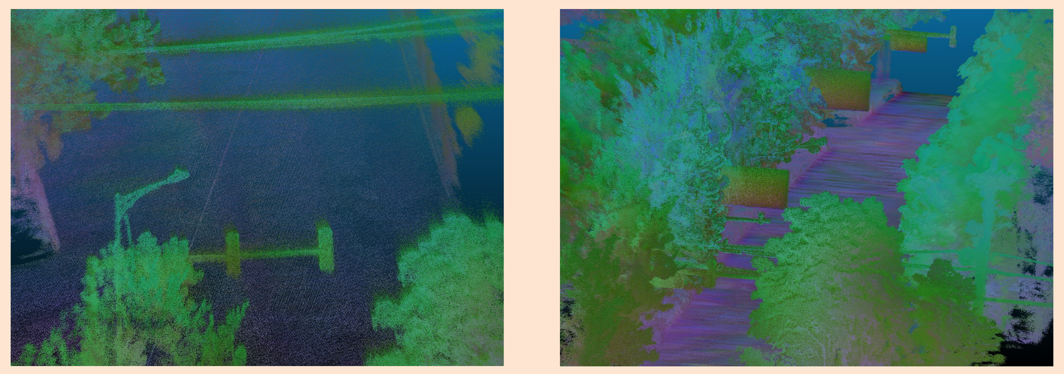
- **FCU-Net**
  - Dense feature extraction from each image
- **Backproject**
  - 3D location of each feature from ground truth pose and depth
- **Merge**
  - Final voxel descriptor is average of all candidates



Original Map



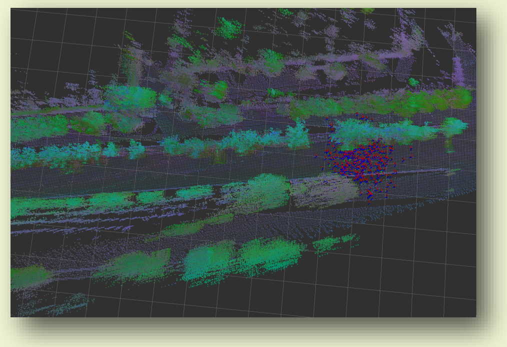
Feature embedded map



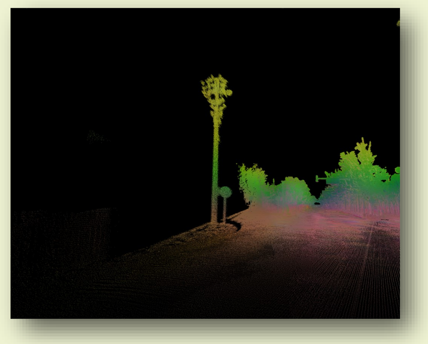
Embedded map details

6 - Deep Imagination localiser

- **Monte Carlo** localisation
  - Represent pose with 6 DOF
  - Each particle represents **one pose hypothesis**
- Particle **"imagined"** views
  - **Project** map onto each particle's **prior pose**
  - Take **depth** into account for **size and occlusion**

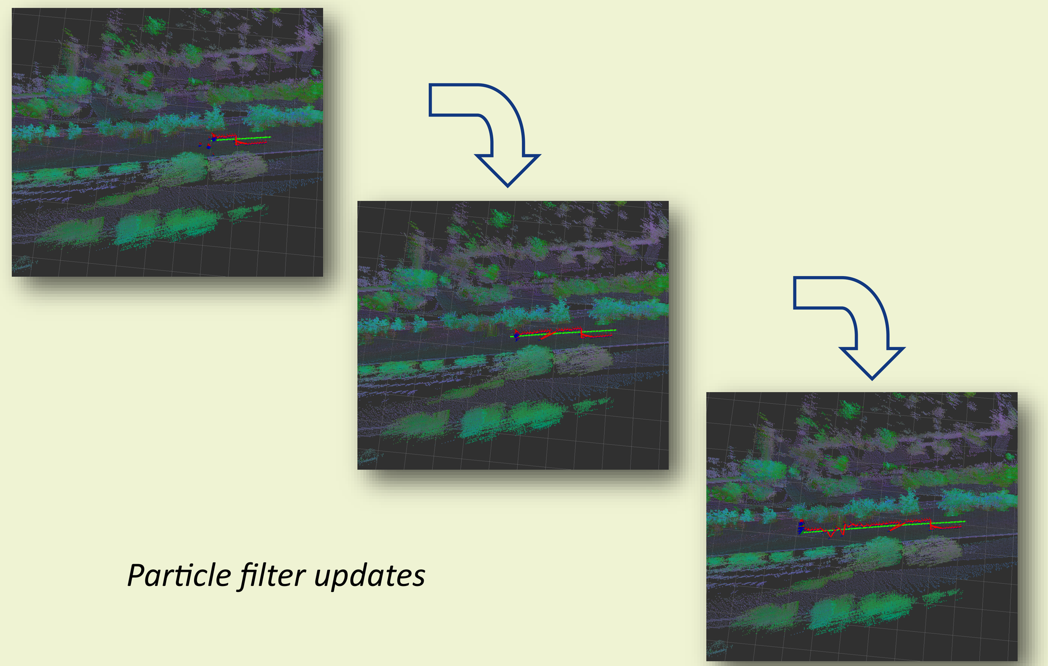


Particle filter initialization



Deep imagined view

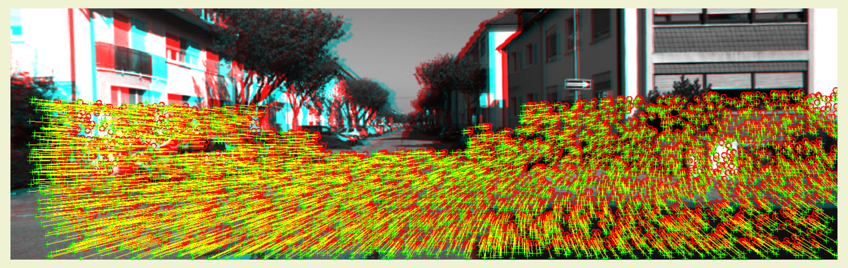
- Particle **likelihood** computation
  - **RMSE** between observation & imagined view
- Particle **weight update**
  - Combine likelihood and VO motion estimation
  - **Approximate MAP** encoding prior and likelihood



Particle filter updates

7 - Visual odometry

- **Essential matrix** estimation given I_t & I_{t-1}
  - **ORB** feature matching
- 4 possible **R**, **t** combinations
  - Combination with most points in front of camera



Sample dataset odometry

8 - Results

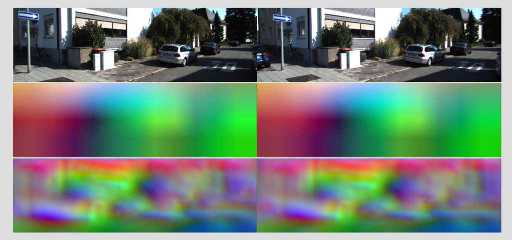
8.1 - Dense feature representation

- **Generic** features
  - Comparable results, **regardless of dataset trained on**

D	$Train$	$Test$	μ_{match}	$\mu_{non-match}$	$\mu_{overlap}$	D	$Train$	$Test$	μ_{match}	$\mu_{non-match}$	$\mu_{overlap}$
3			0.107	1.156	0.131	3			0.129	1.075	0.109
10	K	K	0.103	1.034	0.138	10	A	K	0.133	0.977	0.124
32			0.103	1.035	0.139	32			N/A	N/A	N/A
3			0.212	0.803	0.162	3			0.201	1.343	0.126
10	K	A	0.222	0.771	0.161	10	A	A	0.192	1.174	0.111
32			0.235	0.693	0.183	32			N/A	N/A	N/A

*Average distance between similar/dissimilar pairs. (**K**itti vs. **A**polloScape train/test)*

- Skip connections increases descriptor resolution

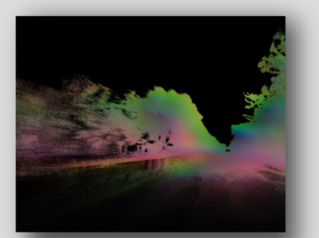


Top: Images - Mid: Base FCN - Bottom: FCU-N (skip)

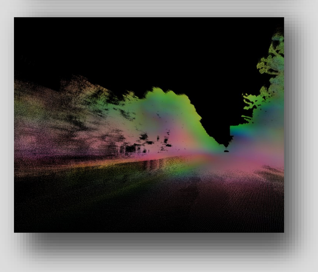
8.2 - Deep Imagination

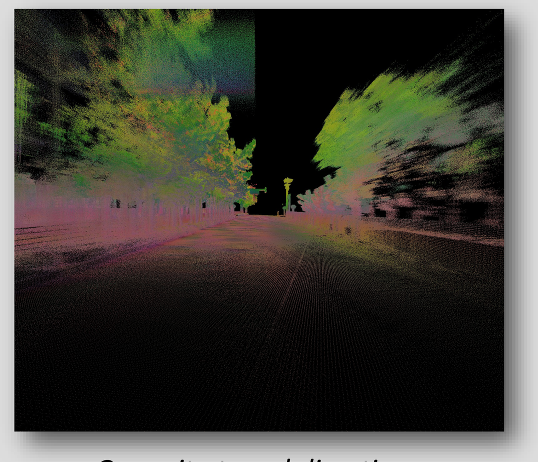
- **Novel imagined viewpoints**

Ground truth



Imagined





Opposite travel direction

- Sequence location prediction

Estimated path over ApolloScape validation sequence

9 - Conclusions

- **Deep Imagination** localiser generates feature representations for **unseen viewpoints.**
- Build a **representation of an environment** and imagine what it looks like from any new position **after a single visitation**.
- Generic features means **no additional training** is required in new environments
- Further improvements from a more sophisticated pose likelihood estimation (**PnP**) or additional motion models (**non-holonomic constraints**)

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