Improved Visual Relocalization by Discovering Anchor Points

Soham Saha   Girish Varma   C.V. Jawahar

Flipkart

IIIT, HYDERABAD

CVIT

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The Visual Relocalization Problem

- Given an image, predict 6-DOF of camera. That is
  - location [3 spatial coordinates]
  - pose [3 angles].

- Needed in Autonomous Navigation applications since
  - GPS is noisy and doesn't work indoors
  - Gives redundancy, in case GPS fails.

Cambridge Landmarks (Outdoor)

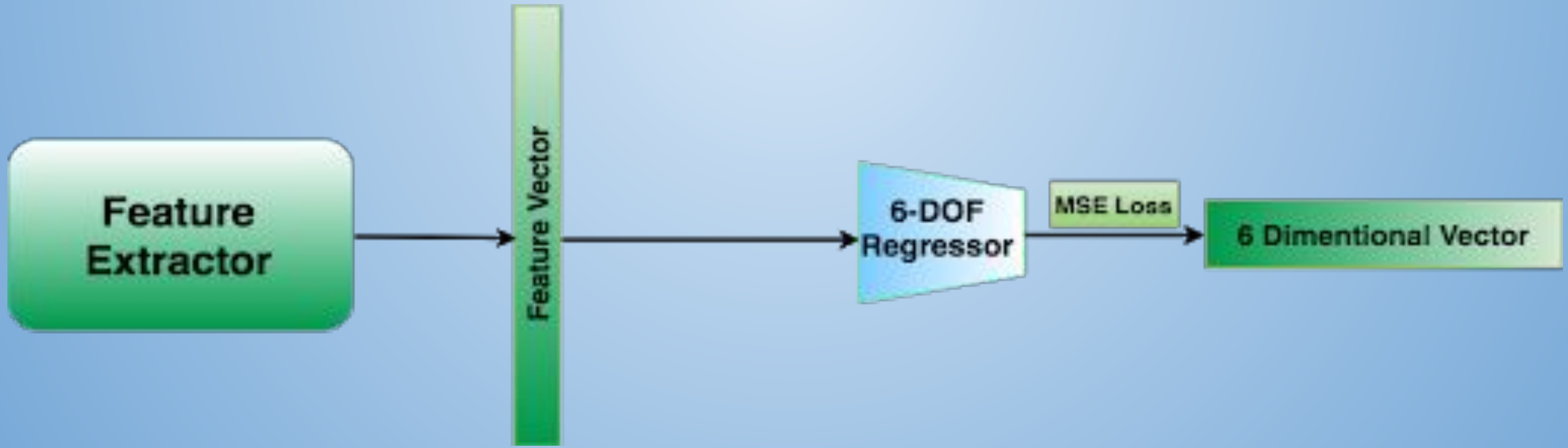
→ 6-DOF Coordinates

7 Scenes (Indoor)

→ 6-DOF Coordinates

DNN based approaches

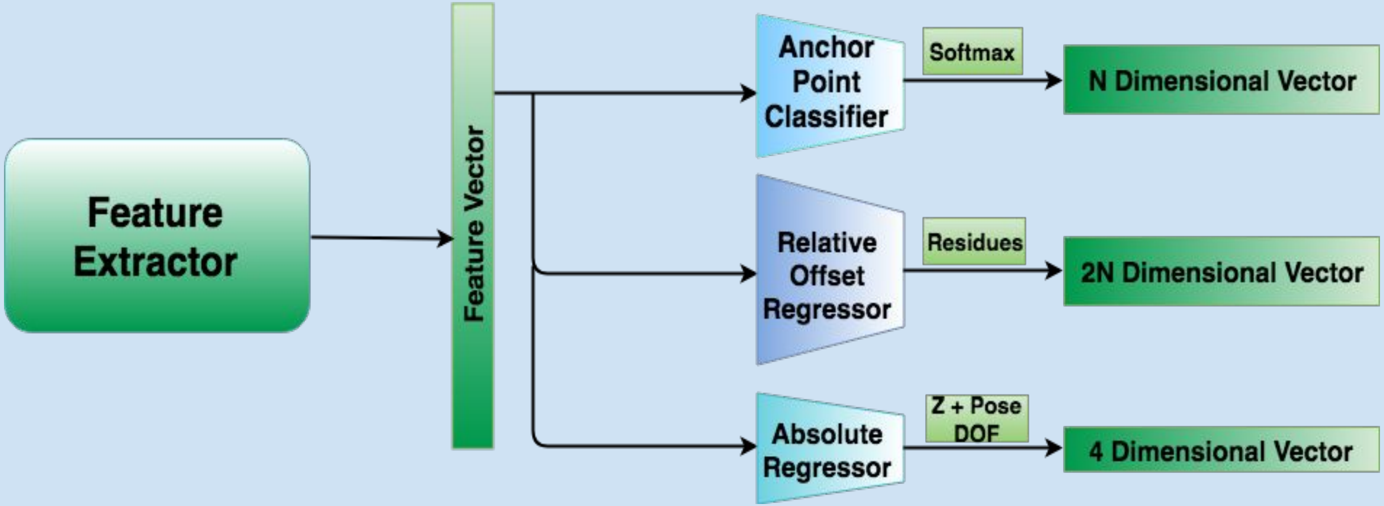
- Image Retrieval Based:
  - Extract image features for all images in dataset.
  - Compute nearest neighbour
- PoseNet approach:
  - Use neural network to directly predict 6-DOF.
  - Train DNN by regressing against ground truth 6-DOF in dataset.



Defining Anchor Points

- Humans typically identify their location relative to other locations or landmarks.
- Inspired from this, we propose an end to end trainable model.
- Define landmarks as anchor points and predict distances relative to them.

Anchor Point based Approach



What is the ground truth for classification?

Is it the nearest anchor point?

Can we discover the most relevant anchor point?

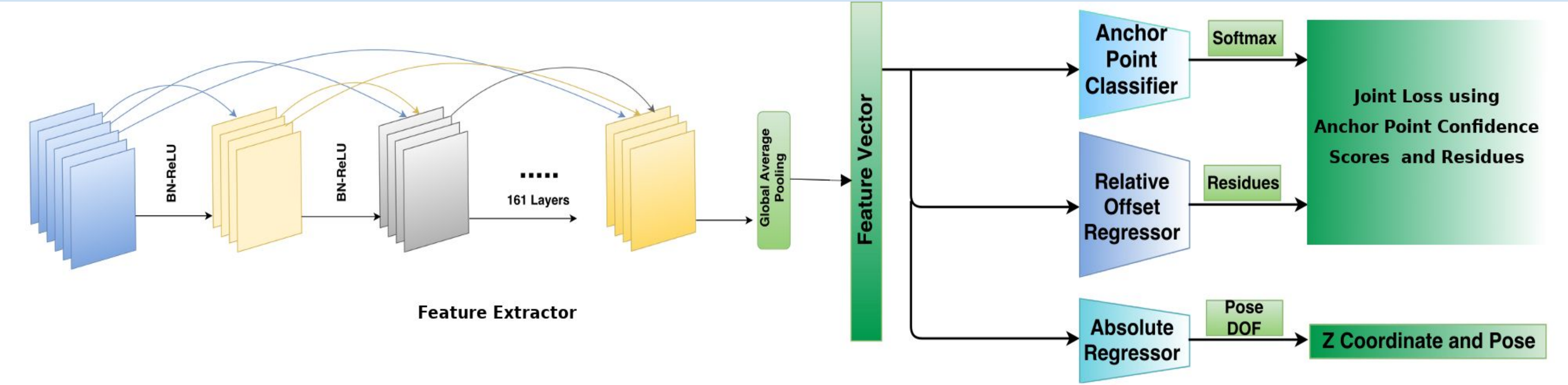
Discovering Relevant Anchor Points

- We have ground truth for all the anchor points.
- We predict the offsets with respect to all of those anchor points.
- Use classification head as confidence score and do a Weighted MSE loss.

Frame Coordinates <X,Y>	Anchor points Coordinates <X,Y>	Offsets <X,Y>
4.25m, 7.51m [Reference Frame]	3.15m, 6.75m [Anchor point 1]	1.10m, 0.76m
	3.60m, 7.00m [Anchor point 2]	0.65m, 0.51m
	4.05m, 7.25m [Anchor point 3]	0.20m, 0.26m
	4.50m, 7.50m [Anchor point 4]	0.25m, 0.01m

Example of offsets to be predicted for 4 Anchor Points

Network Architecture



Loss Function

$$Loss = \alpha_1 \underbrace{H(C_i, \hat{C}_i)}_{\text{Cross-Entropy loss component}} + \underbrace{\alpha_2 \sum_i \left[\left(X_i - \hat{X}_i\right)^2 + \left(Y_i - \hat{Y}_i\right)^2 \right] C_i}_{\text{Offsets weighted by Confidence}} + \underbrace{\alpha_3 \sum_i \left[\left(Z_i - \hat{Z}_i\right) \right]^2}_{\text{Z- coordinate Regressor}} + \underbrace{\left\| P_i - \frac{\hat{P}_i}{\|\hat{P}_i\|} \right\|^2}_{\text{Pose Regressor}}$$

Selected Quantitative Results

Scene	Area or Volume	Posenet Geom. Rep. [11]	Ours (DenseNet) (w/o cross entropy)	**Ours (GoogleNet) (w/o cross entropy)**
Great Court	$8000m^2$	$6.83m, 3.47°$	$4.64m, 3.42°$	**$5.89m, 3.53°$**
King's College	$5600m^2$	$0.88m, 1.04°$	$0.57m, 0.88°$	**$0.79m, 0.95°$**
Old Hospital	$2000m^2$	$3.20m, 3.29°$	$1.21m, 2.55°$	**$2.11m, 3.05°$**
Shop Facade	$875m^2$	$0.88m, 3.78°$	$0.52m, 2.27°$	**$0.77m, 3.25°$**
St. Mary's Church	$4800m^2$	$1.57m, 3.32°$	$1.04m, 2.69°$	**$1.22m, 3.02°$**
Street	$50000m^2$	$20.3m, 25.5°$	$7.86m, 24.2°$	**$11.8m, 24.3°$**
Chess	$6m^2$	$0.13m, 4.48°$	$0.06m, 3.89°$	**$0.08m, 4.12°$**
Fire	$2.5m^2$	$0.27m, 11.3°$	$0.15m, 10.3°$	**$0.16m, 11.1°$**
Head	$1m^2$	$0.17m, 13.0°$	$0.08m, 10.9°$	**$0.09m, 11.2°$**
Office	$7.5m^2$	$0.19m, 5.55°$	$0.09m, 5.15°$	**$0.11m, 5.38°$**
Pumpkin	$5m^2$	$0.26m, 4.75°$	$0.10m, 2.97°$	**$0.14m, 3.55°$**
Red Kitchen	$18m^2$	$0.23m, 5.35°$	$0.08m, 4.68°$	**$0.13m, 5.29°$**
Stairs	$7.5m^2$	$0.35m, 12.4°$	$0.10m, 9.26°$	**$0.21m, 11.9°$**

Selected Quantitative Results

Scene	DenseNet (Feature Extractor)		GoogleNet (Feature Extractor)		MobileNet (Feature Extractor)	
	Performance	**FLOPs**	**Performance**	**FLOPs**	**Performance**	**FLOPs**
Kings College	$0.57m$, 0.88°	5998 M	$0.79m$, 0.95°	760 M	$0.67m$, 0.94°	569 M
Shop Facade	$0.52m$, 2.27°		$0.77m$, 3.25°		$0.60m$, 2.31°	

Selected Qualitative Results

Scene	Input Frame	Nearest Anchor Point	Learned Anchor Point
Great Court			
King's College			
Old Hospital			

THANK YOU!

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Actively looking for PhD opportunities!

sohamsaha.cs@gmail.com