Unsupervised Alignment Network

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AIMS
Autonomous Intelligent Machines & Systems

Motivation:

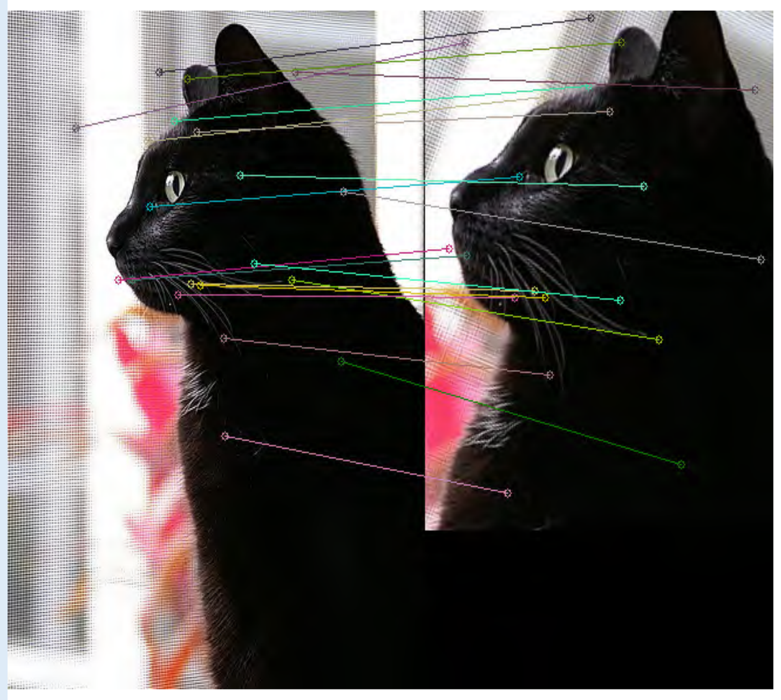


Image alignment is a classical task that involves finding correspondences and inferring geometric transformation that maps a given source image to a target image.

- Current methods lack robustness and fail to align the complex and ambiguous cases.

Contributions:

- Unsupervised **robust** alignment network that emphasises relevant features and handles outliers.
- **Burstiness** module that penalises the repetitive regions or the textures within the image.

Self-Burstiness:

Consider an image $I \in \mathcal{R}^{M \times N}$ and its feature representation $\mathcal{F}_I \in \mathcal{R}^{M \times N \times D}$

For $(i,j) \in I$

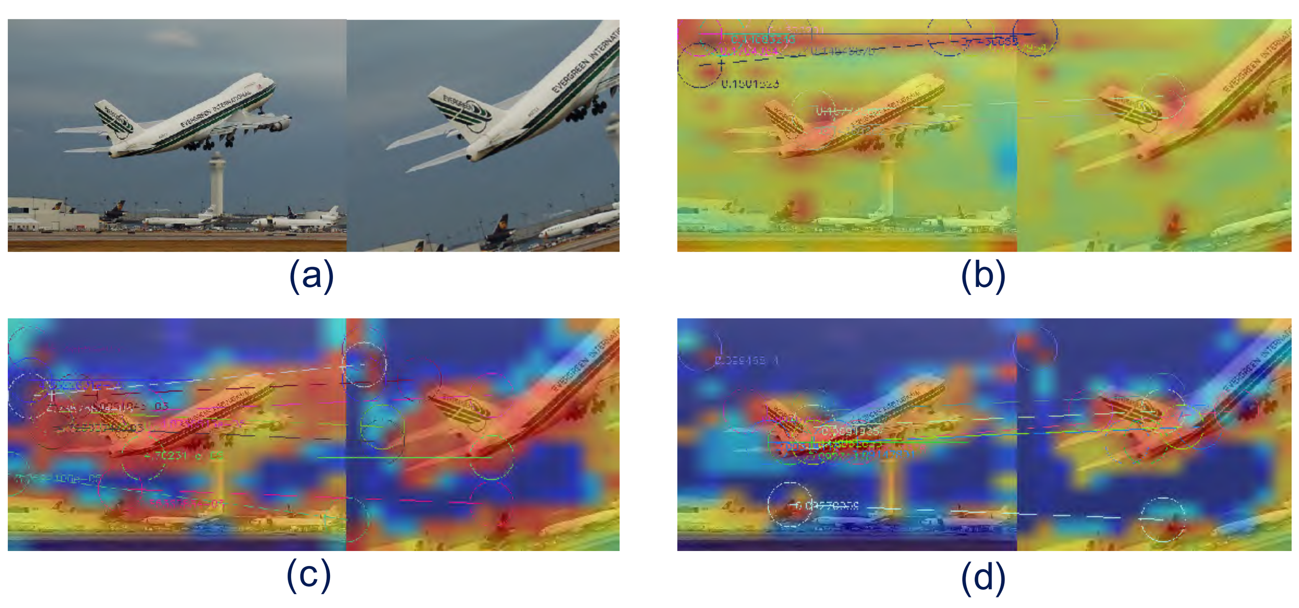
$$U_{i,j}{}^{I} = softmax(-\boxed{\mathcal{B}^{I}{}_{r}(f_{i,j})})$$

Repetitiveness of the feature $f_{i,j}$ within the open ball $\mathcal{B}^{I}{}_{r}(f_{i,j})$

$$\mathcal{B}^{I}{}_{r}(f_{i,j}) = \{f_{k,l} \in \mathcal{F}_I / ||f_{i,j} - f_{k,l}||_2 < r\}$$

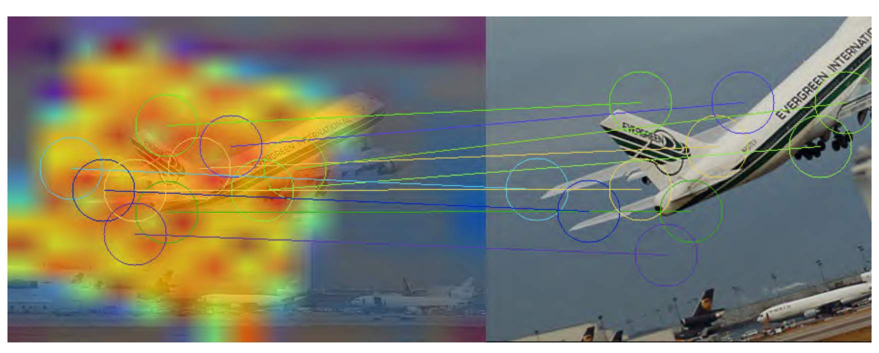
- Burstiness-based matching score for each $(i,j) \in I_{src}$, $(k,l) \in I_{tgt}$

$$\boxed{s_{i,j,k,l}{}^{I_{src},I_{tgt}} = < f_{i,j} \odot U_{i,j}{}^{I_{src}}, f_{k,l} \odot U_{k,l}{}^{I_{tgt}} >}$$



(a): original pair of images with the source (left) and the target (right), (b): the best matching scores and the top correspondences without self-burstiness, in (c) with self-burstiness r = 0.9 and (d) with self-burstiness r = 0.8

RANSAC-like inlier mask:



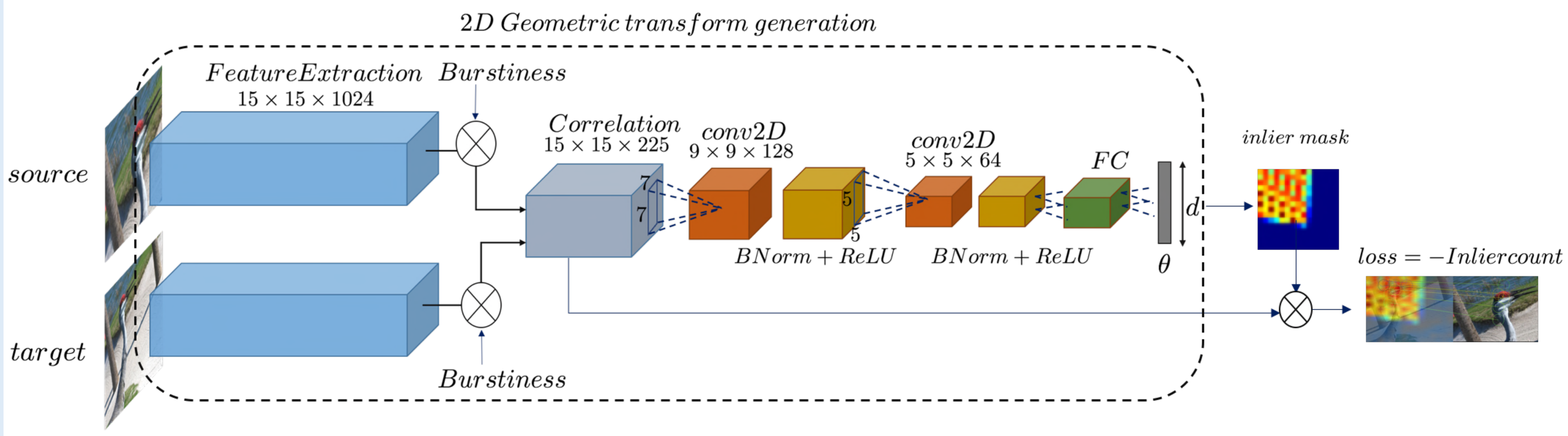
For each $(i,j) \in I_{src}$, $(k,l) \in I_{tgt}$

$$\boxed{m_{i,j,k,l} = \left\{ \begin{array}{ll} 1 & if ||(i,j) - \mathcal{T}^{-1}{}_{\theta}(k,l)||_2 < l \\ 0 & otherwise \end{array} \right\}}$$

Model:

End-to-end alignment network including:

- A pre-trained feature extraction convolutional neural network (VGG-16, ResNet-101)
- A burstiness module (downweights irrelevant features)
- 2D geometric transform generation (convolutional regression network)
- A differentiable RANSAC-like inlier count (inlier mask)



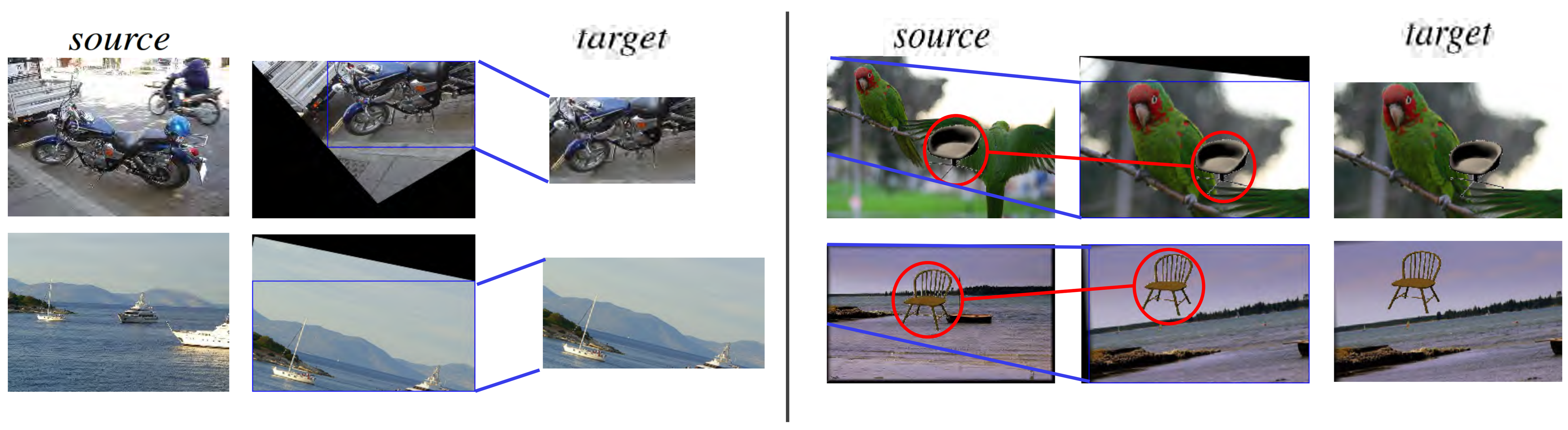
Loss function:

$$\boxed{\mathcal{L}_{inliers} = - \sum_{(i,j) \in I_{src}} \sum_{(k,l) \in I_{tgt}} s_{i,j,k,l}{}^{I_{src},I_{tgt}} m_{i,j,k,l}}$$

Hala Lamdouar – Unsupervised Alignment Network

Challenging dataset:

- 2 different transformations for the background (PASCAL VOC2011) and the foreground (3D rendered chairs)
- Cropping with respect to the maximal inscribed axis-aligned rectangle



Results:

We use the PCK measure (percentage of correct points) i.e. the number of points where:

$$||\mathcal{T}_{\theta}(i,j) - \mathcal{T}_{\theta_{GT}}(i,j)||_2 < l$$

On PF-PASCAL dataset:

class/method	VGG-16 -affine	ResNet-101-affine	VGG-16-affine+TPS	ResNet-101-affine+TPS	VGG-16 -affine+Burstiness	ResNet-101-affine+Burstiness	VGG-16-affine+TPS+Burstiness	ResNet-101-affine+TPS+Burstiness
aeroplane	50.40%	50.98%	50.37%	44.53%	50.76%	44.92%	**51.15%**	18.58%
bicycle	42.61%	43.23%	43.20%	38.50%	**43.49%**	39.30%	41.41%	12.90%
bird	31.67%	28.26%	**36.44%**	30.76%	32.47%	32.70%	34.62%	20.88%
boat	27.78%	30.56%	26.85%	19.44%	22.22%	**33.33%**	25.00%	23.15%
bottle	39.17%	10.00%	37.92%	16.25%	**47.08%**	42.08%	46.25%	5.83%
bus	49.07%	41.65%	49.85%	37.48%	51.28%	46.26%	**52.33%**	8.46%
car	51.51%	43.32%	**52.83%**	42.71%	48.36%	38.73%	48.14%	12.53%
cat	30.30%	28.05%	29.33%	**34.04%**	30.20%	29.51%	30.04%	25.47%
chair	36.35%	25.24%	37.54%	27.38%	33.49%	**38.65%**	35.63%	13.41%
cow	65.56%	54.44%	65.56%	65.56%	**71.11%**	52.22%	**71.11%**	12.22%
diningtable	33.93%	28.57%	32.14%	25.60%	**39.29%**	28.57%	35.71%	16.07%
dog	29.05%	27.94%	28.35%	30.17%	27.94%	**32.46%**	29.57%	22.67%
horse	30.18%	22.00%	30.18%	21.47%	**33.72%**	27.24%	31.87%	21.61%
motorbike	41.62%	**40.90%**	40.86%	35.77%	42.33%	39.40%	40.51%	12.00%
person	26.65%	24.23%	28.50%	26.13%	**28.76%**	25.21%	26.95%	17.36%
pottedplant	31.04%	28.96%	33.54%	28.96%	31.67%	22.29%	**34.79%**	18.33%
sheep	**80.00%**	40.00%	**80.00%**	**80.00%**	**80.00%**	60.00%	**80.00%**	0.00%
sofa	37.82%	**47.65%**	39.25%	32.61%	39.58%	37.04%	38.78%	14.17%
train	**40.00%**	**40.00%**	39.00%	36.00%	38.00%	31.00%	39.00%	5.00%
tvmonitor	20.11%	13.00%	22.11%	14.89%	27.11%	**27.67%**	29.56%	1.11%
total	38.26%	34.55%	38.64%	33.06%	39.10%	35.96%	**39.17%**	14.35%

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