Force Banner for the recognition of spatial relations

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Introduction

- We consider the general task of the description of a scene in a 2D image.
- Common approaches: "bag-of-objects/features", CNNs, deformable parts models...
- But common features (shape, texture, points, "deep features"...) are not sufficient to describe complex objects/scenes and to model spatial configurations.

$\Rightarrow$ Interest of considering spatial relations between objects.

Segmented scene from the *CityScapes* dataset.

Aerial scene from the ICG drone dataset.

Scene from the *SpatialSense* dataset, with annotation *"street under bus"*.

Two ways to characterize spatial relations:

- evaluation of spatial relations in natural language (ex: to the left of, above, in...)
- **relative position descriptors** which aim at giving a complete description of the configuration, and which can be translated into spatial relations in natural language.

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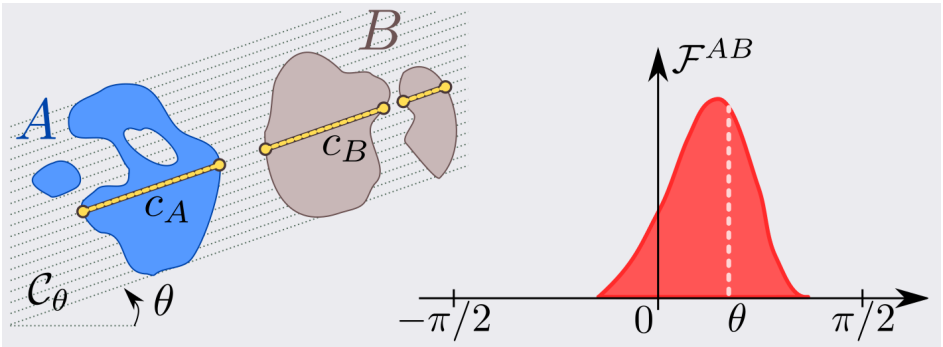
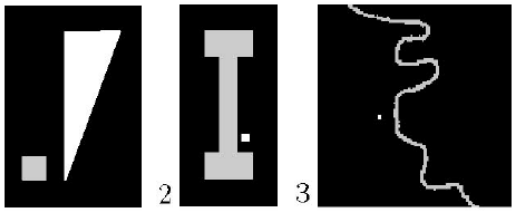
From Force Histogram to Force Banner

- The force histogram is a relative position descriptor, robust to similitudes (pose variation).

  For a given direction θ and a given force r, it integrates $\varphi_r(d) = \frac{1}{d^r}$ the attraction force between two points.



Force histogram computation (from [Matsakis et Wendling, 1999]).



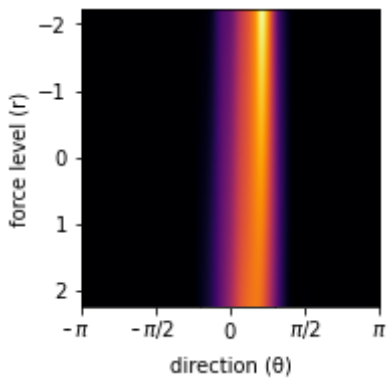
	1		2		3	
	M0	M2	M0	M2	M0	M2
Right	41	**64**	38	**58**	03	02
Left	00	00	05	07	51	**75**
Above	**60**	40	56	48	37	21
Below	05	05	**67**	33	**59**	28

F0 and F2 opinions in ambiguous configurations.

- It was proposed for a single force, providing variable opinions [Matsakis et Wendling, 1999].
- We suggest to extend it to a range of force levels, which makes a continuous 2D descriptor:

$$FB^{AB} : [0, 2\pi[\times [r_s, r_e] \to \mathbb{R}_+$$
$$(\theta, r) \mapsto F_r^{AB}(\theta)$$

This provides a more complete description, which can be used as input of a CNN.



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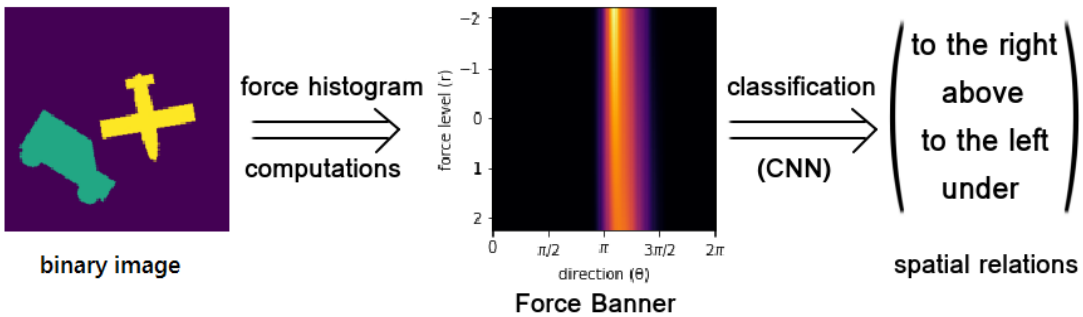
Translation to spatial relations

Such relative position descriptors can be used for the recognition of spatial relations.
We propose to use the Force Banner in a learning scheme with a CNN:



Experimental settings

Task: classification of simple spatial relations (4 classes: right, left, above, under)

- data: 2 synthetic datasets (2 280 images) + test on patches from a remote sensing image
- model: SqueezeNet pre-trained on ImageNet and fine-tuned / trained from scratch
- baselines: same CNN trained on the raw images / MLP on the bounding box coordinates

Samples of images from our 3 experimental datasets.

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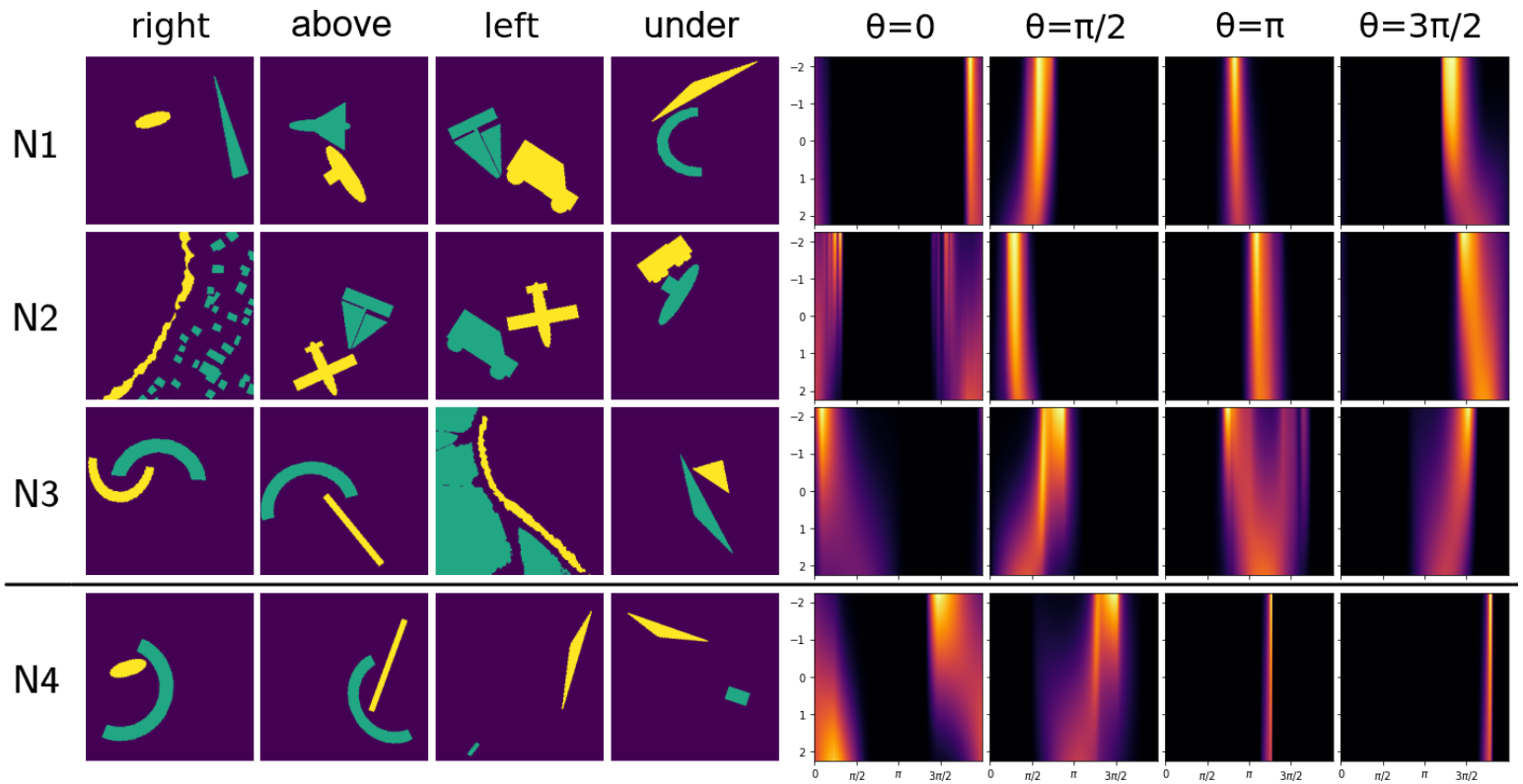
Preliminary results

- Dataset generation with various simple shapes and random positions, orientations and scales
- Manual annotation: class + level of difficulty (from N1 to N4)
- Force Banner computation: force level from -2.12 to 2.12



Samples of input images and force banners for each class and each difficult level.

Classification results

Train & Test on synthetic images (SimpleShapes), using different subsets of difficulty levels + 1 test on the remote sensing image (GIS)

	dF-banner		*bbox image*		*dFB + image*		*bbox coords*	
Datasets	**OA**	**STD**	**OA**	**STD**	**OA**	**STD**	**OA**	**STD**
Train & Test on N1	**92.66%**	0.94%	88.39%	0.50%	92.13%	0.25%	90.73%	1.71%
Train & Test on N1+N2	92.70%	0.62%	87.53%	0.46%	**92.90%**	0.78%	90.13%	0.34%
Train & Test on N1+N2+N3	91.47%	1.36%	87.30%	0.55%	**92.53%**	1.62%	88.96%	0.89%
Train on N1 & Test on N3	76.03%	3.76%	73.86%	1.15%	**78.13%**	2.65%	72.75%	3.46%
Train on N1+N2 & Test on N3	75.54%	2.70%	72.82%	1.54%	**78.55%**	2.79%	73.17%	0.96%
Train on N1+N2+N3 & Test on GIS	**91.81%**	0.79%	61.75%	3.65%	86.02%	2.43%	86.67%	3.17%

Classification results (overall accuracy – OA and standard deviation – STD) on the test sets (on 3 runs).

Analysis:

- good performance of the Force Banner, over both baselines in all test cases
- particularly good on the GIS image $\Rightarrow$ allows to generalize to other kinds of configurations
- relatively low gain of the image in addition to the force banner $\Rightarrow$ complete descriptor

$\Rightarrow$ good descriptor for this task

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Conclusion

- complete representation of spatial configurations, robust to similitudes (pose variation)
- can be easily translated into spatial relations in natural language
- allows to recognize spatial relations with good generalization capacity
- can be associated to other features to provide a complete description of a scene

Perspectives

- more experiments to explore different parameters, classifiers, spatial relations, data...
- deeper analysis of the force levels that are used for given objects configurations
- integration of this descriptor into a larger model to describe a scene with several objects
- use this descriptor between an object and its background to make it a shape descriptor

Scene from the *SpatialSense* dataset, with the annotation *"street under bus"*.

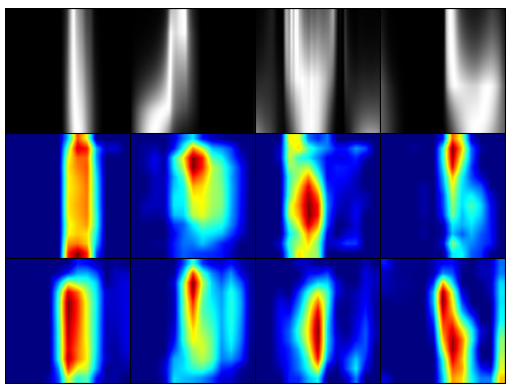

Illustration of GradCam on Force Banners.

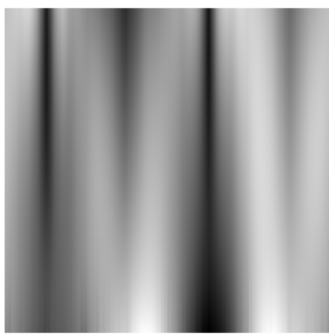

Image from the *Sharvit1* dataset, circular background and force banner.

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