# **COSFIRE MODELS FOR DESCRIBING OBJECTS** AS ARRANGEMENTS OF CIRCULAR REGIONS



International Computer Vision Summer School Gecer B. - Bilkent University, Azzopardi G. - University of Malta, Petkov N. - University of Groningen baris.gecer@cs.bilkent.edu.tr, george.azzopardi@um.edu.mt, n.petkov@rug.nl

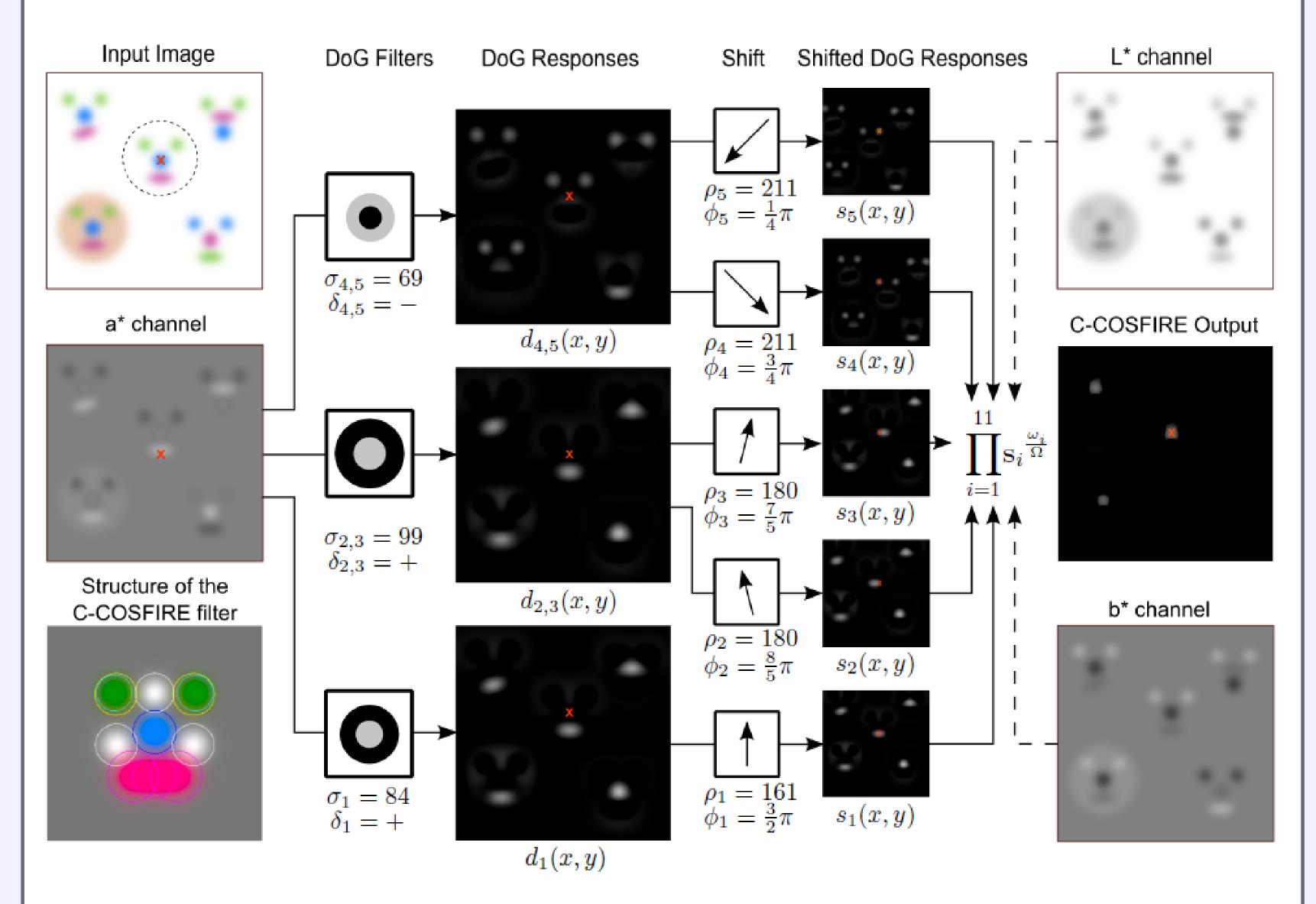
#### Abstract

We propose blob-based C-COSFIRE filters to model a given object of interest in terms of diffuse circular regions in a specific mutual spatial arrangement.

A C-COSFIRE filter combines the responses of a collection of DoG filters of different scales, in all dimensions of a color space, and at certain relative positions. Its parameters are determined in an automatic configuration process that analyses the properties of a given object of interest. We show its effec-

# **Applying C-COSFIRE Filter to an Image**

- Responds where a pattern is present which is similar to the prototype pattern
- Output is computed by the weighted geometric mean of shifted DoG responses

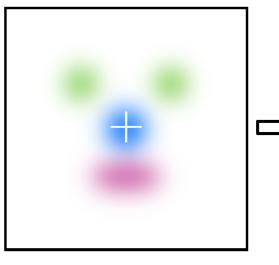


tiveness on two benchmark data sets.

### Automatic Configuration

Main steps :

- 1. Transform a single prototype pattern into a color space (L\*a\*b\*)
- 2. Detect blobs in each color channel using DoG filters
- 3. Extract the properties of the detected blobs (DoG) together with their mutual spatial arrangement.



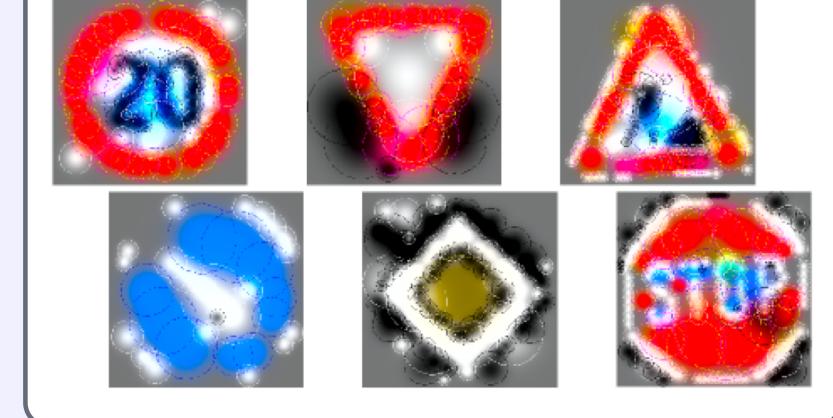
 $(\alpha_1 = a^*, \sigma_1 = 84, \delta_1 = +, \rho_1 = 161, \phi_1 = 3\pi/2),$  $(\alpha_2 = a^*, \sigma_2 = 99, \delta_2 = +, \rho_2 = 180, \phi_2 = 8\pi/5),$  $(\alpha_3 = a^*, \sigma_3 = 99, \delta_3 = +, \rho_3 = 180, \phi_3 = 7\pi/5),$  $(\alpha_4 = a^*, \sigma_4 = 69, \delta_4 = -, \rho_4 = 211, \phi_4 = 3\pi/4),$  $(\alpha_5 = a^*, \sigma_5 = 69, \delta_5 = -, \rho_5 = 211, \phi_5 = \pi/4),$  $(\alpha_6 = b^*, \sigma_6 = 81, \delta_6 = +, \rho_6 = 204, \phi_6 = \pi/4),$  $(\alpha_7 = b^*, \sigma_7 = 81, \delta_7 = +, \rho_7 = 204, \phi_7 = 3\pi/4),$  $(\alpha_8 = b^*, \sigma_8 = 84, \delta_8 = -, \rho_8 = 4, \phi_8 = \pi/2),$  $(\alpha_9 = L^*, \sigma_9 = 81, \delta_9 = +, \rho_9 = 149, \phi_9 = 1.9\pi),$  $(\alpha_{10} = L^*, \sigma_{10} = 81, \delta_{10} = +, \rho_{10} = 150, \phi_{10} = 1.1\pi),$  $(\alpha_{11} = L^*, \sigma_{11} = 75, \delta_{11} = +, \rho_{11} = 150, \phi_{11} = \pi/2)$ 

The above figure shows an example of the processing of the first five tuples of a C-COSFIRE filter whose structure is illustrated at the bottom-left corner :

- 1. Apply mutual three DoG filters to a\* channel
- 2. Shift DoG responses according to the configuration
- 3. Compute the weighted geometric mean of all the shifted DoG filter responses (including L\* and b\* channels)

#### **Configuration Examples Experiments: Traffic Signs and Butterflies**

For both data sets, we follow the following procedure :



#### References

- [1] G. Azzopardi, N. Petkov, Trainable COSFIRE filters for keypoint detection and pattern recognition, in *IEEE PAMI*, 2013
- [2] J. Stallkamp, M. Schlipsing, J. Salmen, C. Igel, The German Traffic Sign Recognition Benchmark: A multi-class classification competition, in *IEEE IJCNN*, 2011
- [3] S. Lazebnik, C. Schmid, J. Ponce, Semi-local affine parts for object recognition, in *BMVC*, 2004

- 1. Configure several C-COSFIRE filters to be selective for patterns (partially or entirely) extracted from the training set.
- 2. Use their responses to form feature vectors
- 3. Train a multi-class SVM classifier with linear kernel.

German Traffic Sign Recognition The Butterfly Data Set [3]: **Benchmark (GTSRB)** Data Set [2] :

- 43 categories, 51839 images
- 98.94% recognition rate is achieved
- Perform better than human subjects

Multi-column deep NN	99.46%
Proposed Method	98.94%
Human Performance	98.84%
Multi-Scale CNNs	98.31%
COSFIRE[1] on gray-scale	90.68%

• 7 categories, 619 images

- 89.02% recognition rate is achieved
- Best performance is 90.4%
- Below, a partial C-COSFIRE filter on a butterfly and its corresponding response for the middle image

