

# Polar representation of covariance descriptors for circular features

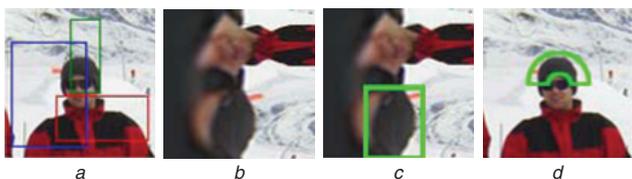
G. Gualdi, A. Prati and R. Cucchiara

The use of polar representation of covariance descriptors, suitable for the classification of circular feature sets, is proposed. It overcomes the implicit limits of state-of-the-art methods based on axis-oriented rectangular patches. The suitability of the proposed solution is verified on two case studies, namely head detection and polymer classification in photomicrograph contexts.

**Introduction:** Object classification exploiting covariance descriptors on Riemannian manifolds [1] has attracted much attention thanks to its broad applicability and high accuracy, e.g. for people detection and texture classification [1, 2]. This approach exploits integral images, used for efficient covariance descriptor computation [2], and axis-oriented rectangular patches (that are sub-windows of the image to classify). When this method is applied to classify objects with non-rectangular shape (e.g. holes, heads, wheels, etc.), the performance in terms of classification accuracy degrades owing to the inclusion of non-discriminative pixels within the rectangular patches.

Locating circles in images has been deeply explored in the literature, for both robotic or industrial applications [3], and 3D object reconstruction or traffic sign recognition [4]. All the proposed methods rely on fitting the pixel values or edge points with a certain parametric function, which is difficult to generalise and heavily affected by the unfavourable correlation between strong false positives and weak true positives [4]. This is a typical limit of parametric approaches, such as Hough transforms. For this reason, [4] proposed to measure a curve's distinctiveness through a one-parameter family of curves, in order to gain in accuracy. Moreover, most of these methods are highly time-consuming, tackling the problem as an optimised search in highly dimensional spaces. In [3] the problem is formulated as a maximum likelihood estimator and the method is proved to be fast and accurate also in the case of occlusions, but it relies on the good extraction of the points describing the curves.

To overcome these problems, this Letter proposes the extension of classification based on covariance descriptors to the case of circular and concave features, by using a polar representation which unrolls the slice of an annulus in a rectangular patch. This approach is suitable also in all cases where the objects to classify are not easily modelled by parametric curves or precise edges cannot be extracted owing to the complexity of the scenes. Finally, this Letter also shows that the computation of covariance descriptors using multi-spectral (colour) image derivatives yields more accurate results than using plain grey-level derivatives, as proposed in [1].



**Fig. 1** Bridging from traditional axis-oriented patches to circular ones, through polar transformation

- a Some rectangular patches used by classifier proposed in [1]
- b Polar transformation of a w.r.t. image centre
- c Rectangular patch on polar image
- d Transformation of patch in c onto original image

**Cascade of boosting classifiers based on covariance descriptors:** Without giving details, the classifier proposed in [1] is based on a rejection cascade of LogitBoost classifiers (the strong classifiers), each composed of a sequence of logistic regressors (the weak classifiers). The domain of the regressors is the space of symmetric matrices, obtained through an exponential mapping from the Riemannian manifold of covariance matrices. Given an input image  $I$  and the following eight-dimensional set  $F$  of features (defined over each pixel of  $I$ ):

$$F = [x, y, |I_x|, |I_y|, \sqrt{I_x^2 + I_y^2}, |I_{xx}|, |I_{yy}|, \arctan(|I_y|/|I_x|)] \quad (1)$$

where  $x$  and  $y$  are the pixel coordinates,  $I_x$ ,  $I_y$  and  $I_{xx}$ ,  $I_{yy}$  are, respectively, the first- and second-order derivatives of the image intensity, the covariance matrices are computed from the set of features  $F$  over axis-oriented rectangular patches of  $I$ . Each weak classifier is associated one-to-one with a rectangular patch (see Fig. 1a).

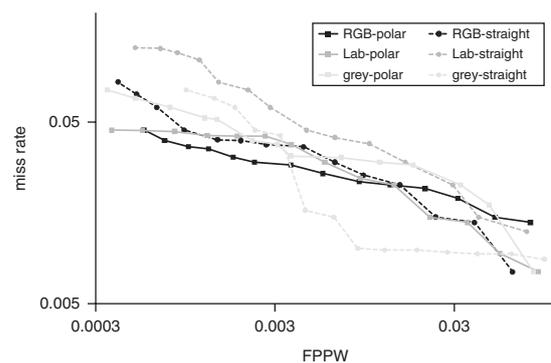
**Polar representation for covariance descriptors:** Aiming to classify circular features, the use of patches with generic circular shapes would catch variations more accurately than just using axis-oriented rectangular shapes. Indeed, using circles or annulus would exclude from the covariance matrix computation all the pixels that do not strictly belong to the circular shape to recognise. To save accurate classification and still exploit integral images (which need axis-oriented rectangular patches), we propose the use of polar images; having defined a reference point  $C(x_c, y_c)$ ,  $\rho^2 = (x - x_c)^2 + (y - y_c)^2$  and  $\vartheta = \arctan((y - y_c)/(x - x_c))$ , the polar image of  $I(x, y)$  w.r.t. to point  $C$  is  $I_p(\rho, \vartheta)$  (see Fig. 1b); given an image with centre  $C$  and its polar transformation (w.r.t.  $C$ ), any slice of annulus on the original image centred in  $C$  can be represented as an axis-oriented rectangular patch on the polar image. Therefore, the polar transformation creates a bridge between the circular patches (useful for classification purposes) and the rectangular patches (needed by the intrinsic classifier architecture); given an image to classify, as a first step the polar image transformation is computed and then the classifiers are applied: the rectangular patches over the polar image, used by the weak classifiers, represent a slice of annulus over the original image, and this provides a classifier more suited to circular shape classification (see Figs. 1c and d).

**Multi-spectral image derivatives for covariance descriptors:** In appearance-based object classification, it is common to avoid the use of chrominance since in most cases colour does not convey any discriminative information. Instead, since colour can be used successfully to compute image derivatives which are more accurate w.r.t. luminance only images [5], we claim that the use of chrominance can improve the classification results. Considering the RGB and Lab colour spaces, in order to compute covariance descriptors sensitive to the chrominance, we define

$$I_x^{RGB} = \sqrt{\left|\frac{\partial R}{\partial x}\right|^2 + \left|\frac{\partial G}{\partial x}\right|^2 + \left|\frac{\partial B}{\partial x}\right|^2}; \quad (2)$$

$$I_{xx}^{RGB} = \sqrt{\left|\frac{\partial^2 R}{\partial x^2}\right|^2 + \left|\frac{\partial^2 G}{\partial x^2}\right|^2 + \left|\frac{\partial^2 B}{\partial x^2}\right|^2}$$

(and by analogy we define  $I_y^{RGB}$ ,  $I_{yy}^{RGB}$ ,  $I_x^{Lab}$ ,  $I_{xx}^{Lab}$ ,  $I_y^{Lab}$ ,  $I_{yy}^{Lab}$ ). Exploiting (2), we then extend (1) to RGB and Lab colour spaces, defining  $F^{RGB}$  and  $F^{Lab}$ .



**Fig. 2** Miss rate (MR) against false positive per window (FPPW) on head images dataset

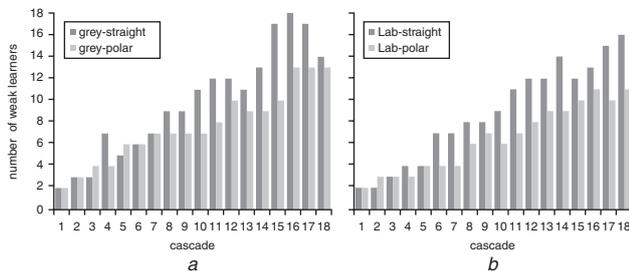
Each marker represents performance up to cascade level. Curves are plotted from cascade 5 (starting at lower right corner) up to 18 (moving towards upper left corner)

**Experimental results:** We tested the proposed approach in head and polymer detection. In the first case, the classifier is applied to find the exact position of the head of pedestrians, after having located them within an image through a pedestrian detector [1]. Candidate head locations are searched around the upper body of the detected pedestrians. In the second case, the classifier is applied to examine photomicrography image datasets and automatically extract the images that

contain polymers. In both cases detection is carried on using a sliding window approach and non maxima suppression of multiple detections is based on meanshift [1]. The training set of the head image dataset is composed of 1162 positive and 2438 negative images. The training set of the micrography images dataset is composed of 2996 positive and 750 negative images. In both datasets, the test set is approximately five times smaller than the training set.

Regarding the head detection, we trained six classifiers: three (called 'straight') using the traditional rectangular patches and three (called 'polar') using the polar transformation. Image derivatives on grey, RGB and Lab values are used in both cases. Each classifier is composed of a rejection cascade with 18 LogitBoost classifiers. Fig. 2 plots the results of the classifiers applied over the testing set. Regardless of the chosen image derivative, the last cascades of the polar classifiers yield better results than the straight classifiers. The use of colour brings further increase in performance: the polar classifier using Lab has a miss rate (MR) of 4.5% (w.r.t. 7.5% of the straight classifier over grey values [1]), a false positives per window (FPPW) of 0.037% (w.r.t. 0.135%) and 33.5% less weak classifiers.

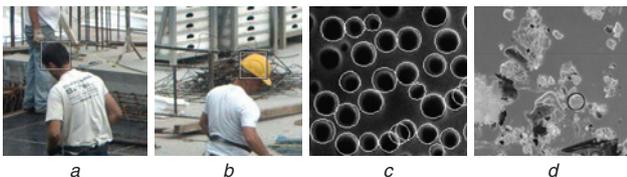
Moreover, the proposed method generates lighter classifiers that will benefit the detection process with a lower computational load (on average, polar classifiers use 23% less weak classifiers; see Fig. 3).



**Fig. 3** Number of weak classifiers per cascade for straight and polar classifier

a With grey image derivatives  
b With Lab image derivatives

Regarding polymer classification, we do not exploit any multi-spectral image derivative since the dataset contains only grey-level images. On average, the MR of the polar classifier is two orders of magnitude lower than the straight classifier (Table 1): this can be explained given the clear circular shape of the polymer bubbles that strongly benefits from the polar representation. Fig. 4 shows visual examples of detection of heads in complex scenarios and of polymer bubbles in the photomicrography dataset.



**Fig. 4** Examples of detections

Correct head detection (a,b) and photomicrography classification (c,d): c detection over polymer image (showing a few missed detection); d detection over non-polymeric image (showing a false positive detection)

**Table 1:** Results on micrography images dataset. Comparison of FPPW performance between polar and straight classifiers w.r.t. given MRs

Miss rate	$10^{-2}$	$10^{-3}$	$10^{-4}$
	<b>FPPW</b>		
<b>Straight classifier</b>	$1.32 \times 10^{-2}$	$29.12 \times 10^{-2}$	$33.68 \times 10^{-2}$
<b>Polar classifier</b>	$0.05 \times 10^{-2}$	$0.15 \times 10^{-2}$	$0.29 \times 10^{-2}$

*Conclusions:* Polar covariance descriptors are proved to be effective for circular shape classification. Further classification accuracy is obtained exploiting multi-spectral image derivatives. These proposed methods have the additional advantage of generating classifiers with a reduced number of weak classifiers.

© The Institution of Engineering and Technology 2010

8 January 2010

doi: 10.1049/el.2010.0021

One or more of the Figures in this Letter are available in colour online.

G. Gualdi and R. Cucchiara (*Department of Engineering of Materials and the Environment, University of Modena and Reggio Emilia, via Vignolese, 905-41100 Modena, Italy*)

A. Prati (*Department of Engineering Sciences and Methods, University of Modena and Reggio Emilia, via G. Amendola, 2-Pad, Morselli 42100, Reggio Emilia, Italy*)

E-mail: andrea.prati@unimore.it

## References

- 1 Tuzel, O., Porikli, F., and Meer, P.: 'Pedestrian detection via classification on Riemannian manifolds', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2008, **30**, (10), pp. 1713–1727
- 2 Tuzel, O., Porikli, F., and Meer, P.: 'Region covariance: a fast descriptor for detection and classification', *Lecture Notes Comput. Sci.*, 2006, **3952**, pp. 589–600
- 3 Frosio, I., and Borghese, N.A.: 'Real-time accurate circle fitting with occlusions', *Patt. Rec.*, 2008, **41**, (3), pp. 1041–1055
- 4 Chin Cheng, Y.: 'The distinctiveness of a curve in a parameterized neighborhood: extraction and applications', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2006, **28**, (8), pp. 1215–1222
- 5 Brook, A., Kimmel, R., and Sochen, N.A.: 'Variational restoration and edge detection for color images', *J. Math. Imaging Vis.*, 2003, **18**, pp. 247–268