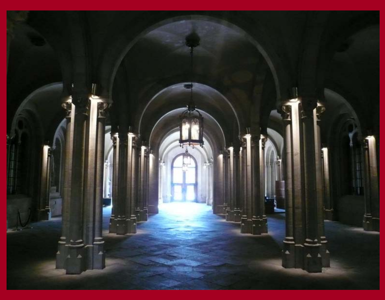

CIRCULAR BLURRED SHAPE MODELS FOR SYMBOL SPOTTING IN DOCUMENTS

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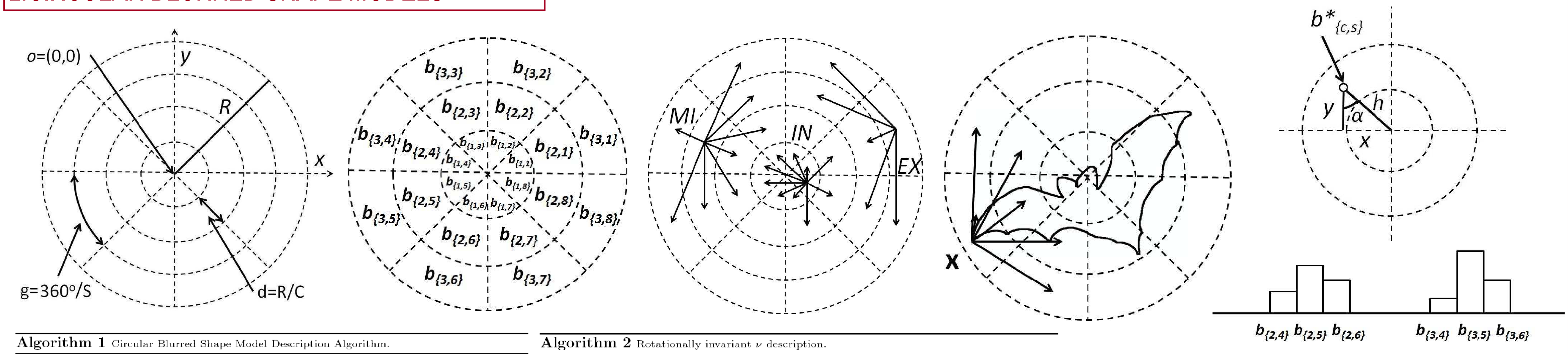
ABSTRACT

Symbol spotting problem requires feature extraction strategies able to generalize from training samples and to localize the target object while discarding most part of the image. In the case of document analysis, symbol spotting techniques have to deal with a high variability of symbols' appearance. In this paper, we propose the Circular Blurred Shape Model descriptor. Feature extraction is performed capturing the spatial arrangement of significant object characteristics in a correlogram structure. *Shape information from objects is shared* among correlogram regions, being tolerant to the irregular deformations. Descriptors are learnt using a cascade of classifiers and Abadoost as the base classifier. Finally, symbol spotting is performed by means of a windowing strategy using the learnt cascade over plan and old musical score documents. Spotting and multi-class categorization results show better performance comparing with the state-of-the-art descriptors.

1.CIRCULAR BLURRED SHAPE MODELS



Algorithm 1 Circular Blurred Shape Model Description Algorithm.

Require: a binary image I, the number of circles C, and the number of sections S
Ensure: descriptor vector ν

Define $d = R/C$ and $g = 360/S$, where R is the radius of the correlogram, as the distance between consecutive circles and the degrees between consecutive sectors, respectively (Figure 1(a)).
Define $B = \{b_{\{1,1\}},..,b_{\{C,S\}}\}$ as the set of bins for the circular description of I, where $b_{c,s}$ is the bin of B between distance $[(c-1)d, cd)$ with respect to the origin of coordinates o, and between angles $[(s-1)g, sg)$ to the origin of coordinates o and x-axis (Figure 1(b)).
Define $b^*_{\{c,s\}} = (d \sin\alpha, d\cos\alpha)$, the centroid coordinates of bin $b_{\{c,s\}}$, where α is the angle between the centroid and the x-axis, and $B^* = \{b^*_{\{1,1\}},..,b^*_{\{C,S\}}\}$ the set of centroids in B (Figure 1(e)).
Define $X_{b_{\{c,s\}}} = \{b_1,..,b_{cs}\}$ as the sorted set of the elements in B^* so that $d(b^*_{\{c,s\}}, b^*_i) \leq d(b^*_{\{c,s\}}, b^*_j),\ i<j$.
Define $N(b_{\{c,s\}})$ as the neighbor regions of $b_{\{c,s\}}$, defined by the initial elements of $X_{b_{\{c,s\}}}$:

$$N(b_{\{c,s\}}) = \begin{cases} X', |X'| = S+3 & \text{if } b_{\{c,s\}} \in IN \\ X', |X'| = 9 & \text{if } b_{\{c,s\}} \in MI \\ X', |X'| = 6 & \text{if } b_{\{c,s\}} \in EX \end{cases}$$

being X' the first elements of X, and IN, MI, and EX, the inner, middle, and extern regions of B, respectively (Figure 1(c)). Note that different number of neighbor regions appears depending of the location of the region in the correlogram. We consider the own region as the first neighbor.
Initialize $\nu_i = 0,\ i \in [1,..,CS]$, where the order of indexes in ν are:
$\nu = \{b_{\{1,1\}},..,b_{\{1,S\}}, b_{\{2,1\}},..b_{\{2,S\}},..,b_{\{C,1\}},..b_{\{C,S\}}\}$
for each point $\mathbf{x} \in I$, $I(\mathbf{x}) = 1$ (Figure 1(d)) **do**
  for each $b_{\{i,j\}} \in N(b_{\mathbf{x}})$ **do**
    $d_{\{i,j\}} = d(\mathbf{x}, b_{\{i,j\}}) = ||\mathbf{x} - b^*_{\{i,j\}}||^2$
  end for
  Update the probabilities vector ν positions as follows (Figure 1(f)):
  $\nu(b_{\{i,j\}}) = \nu(b_{\{i,j\}}) + \frac{1/d_{\{i,j\}}}{D_{\{i,j\}}},\ D_{\{i,j\}} = \sum_{b_{\{m,n\}} \in N(b_{\{i,j\}})} \frac{1}{||\mathbf{x}-b^*_{\{m,n\}}||^2}$
end for
Normalize the vector ν as follows:
$d' = \sum_{i=1}^{CS} \nu_i,\ \nu_i = \frac{\nu_i}{d'},\ \forall i \in [1,..,CS]$

Algorithm 2 Rotationally invariant ν description.

Require: ν, S, C
Ensure: Rotationally invariant descriptor vector ν^{ROT}

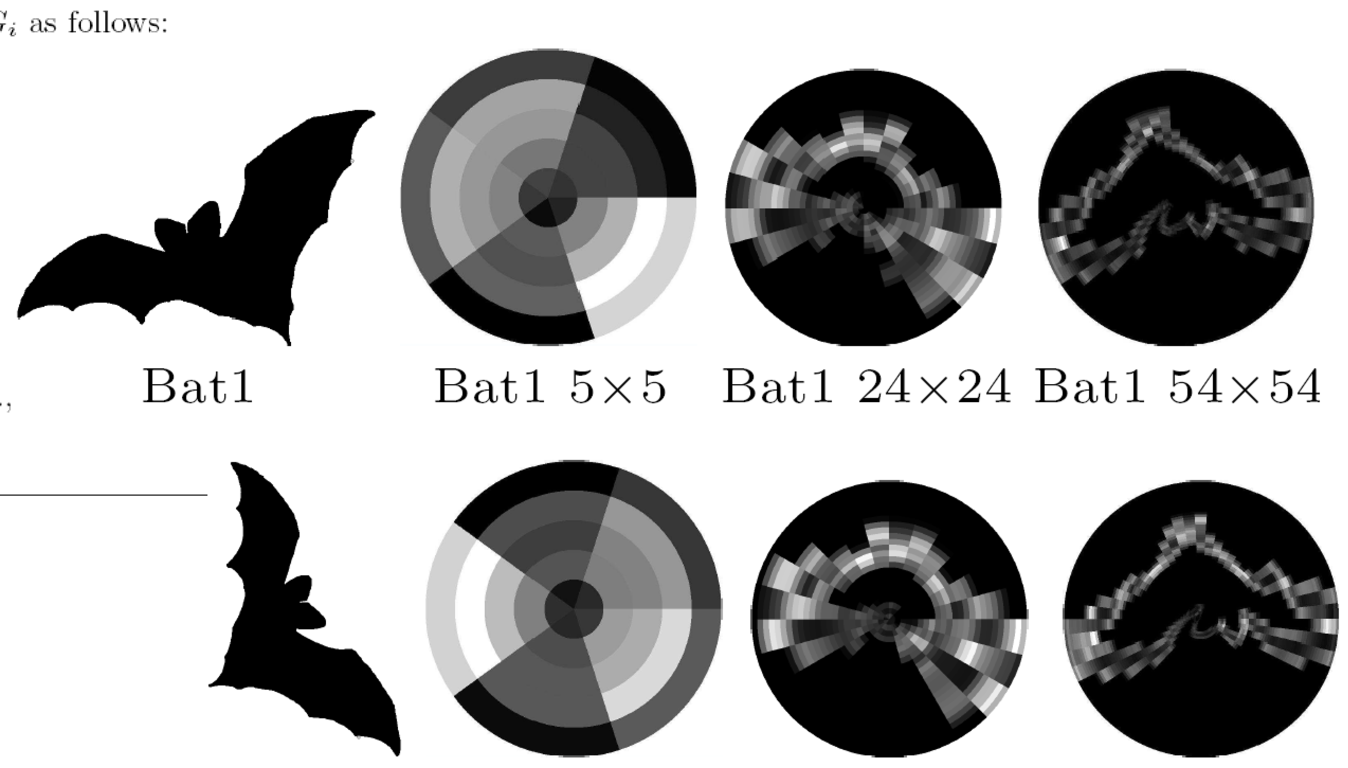
Define $G = \{G_1,..,G_{S/2}\}$ the $S/2$ diagonals of B, where $G_i = \{\nu(b_{\{1,i\}}),..,\nu(b_{\{C,i\}}),..,\nu(b_{\{1,i+S/2\}}),..,\nu(b_{\{C,i+S/2\}})\}$

Select G_i so that $\sum_{j=1}^{2C} G_i(j) \geq \sum_{j=1}^{2C} G_k(j),\ \forall k \in [1,..,S/2]$

Define L_G and R_G as the left and right areas of the selected G_i as follows:
$L_G = \sum_{j,k} \nu(b_{\{j,k\}}), j \in [1,..,C], k \in [i+1,..,i+S/2-1]$
$R_G = \sum_{j,k} \nu(b_{\{j,k\}}), j \in [1,..,C], k \in [i+S/2+1,..,i+S-1]$

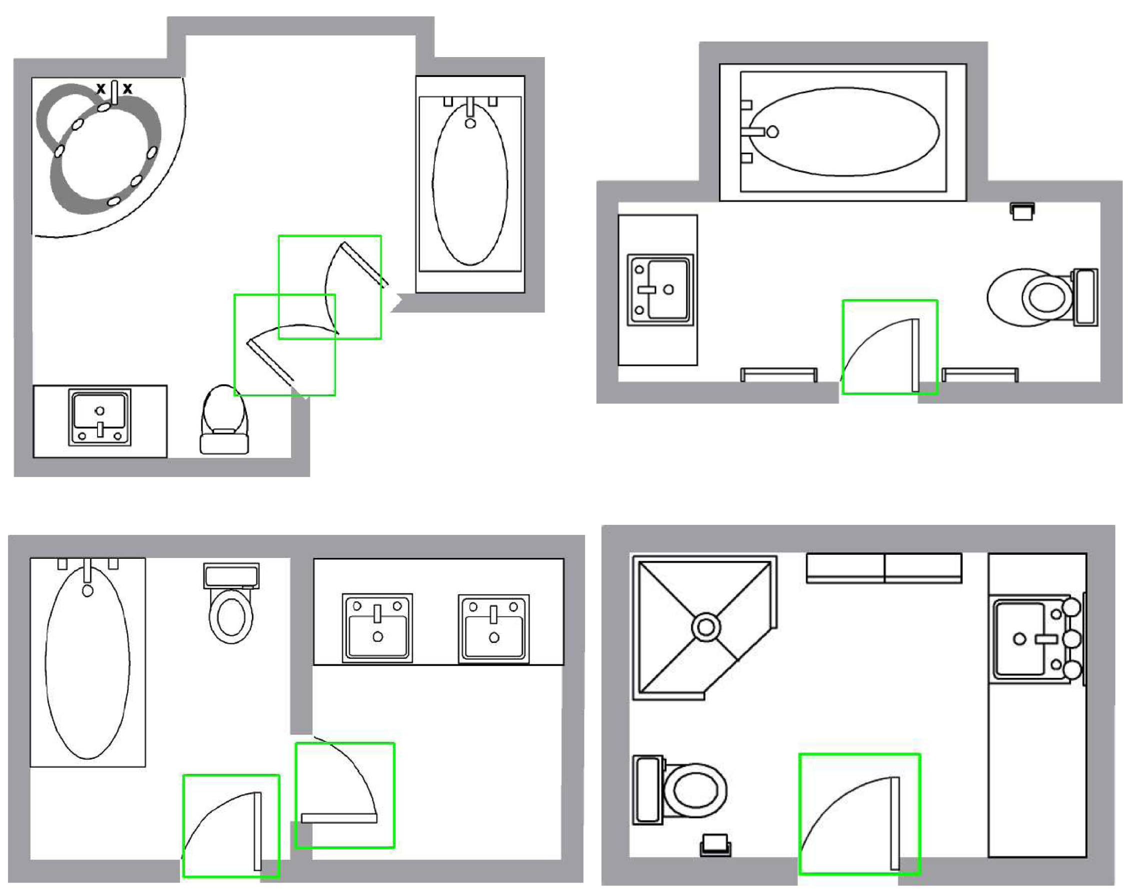
if $L_G > R_G$ **then**
  B is rotated $k = i + S/2 - 1$ positions to the left:
  $\nu^{ROT} = \{\nu(b_{\{1,k+1\}}),..,\nu(b_{\{1,S\}}),\nu(b_{\{1,1\}}),..,\nu(b_{\{1,k\}}),..,$
  $,..,\nu(b_{\{C,k+1\}}),..,\nu(b_{\{C,S\}}),\nu(b_{\{C,1\}}),..,\nu(b_{\{C,k\}})\}$
else
  B is rotated $k = i - 1$ positions to the right:
  $\nu^{ROT} = \{\nu(b_{\{1,S\}}),..,\nu(b_{\{1,S-k+1\}}),\nu(b_{\{1,1\}}),..,\nu(b_{\{1,S-k\}}),..,$
  $,..,\nu(b_{\{C,S\}}),..,\nu(b_{\{C,S-k+1\}}),\nu(b_{\{C,1\}}),..,\nu(b_{\{C,S-k\}})\}$
end if

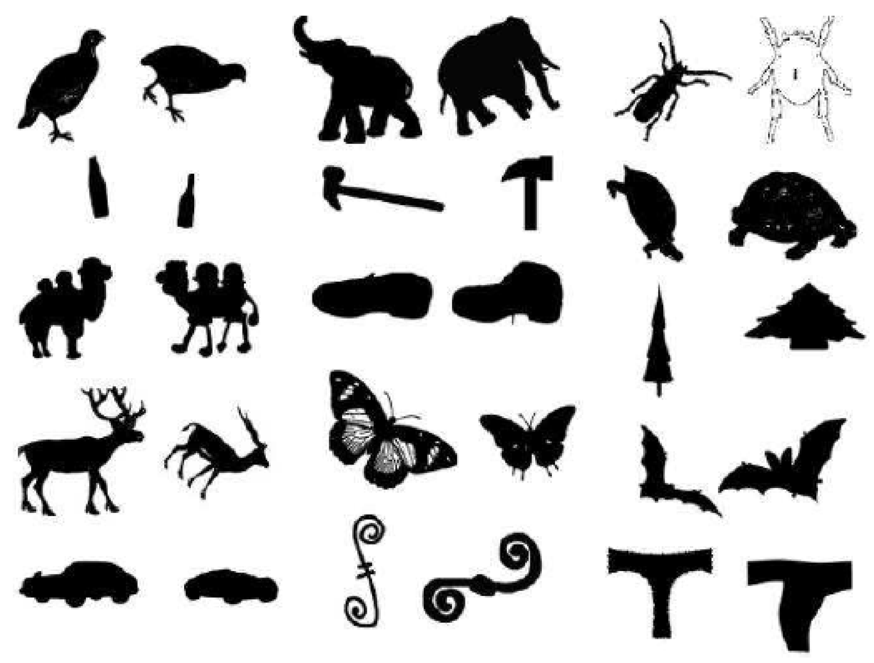
Circular shape descriptor
Rotation invariant
Cascade detector spotting



2.RESULTS

- •20 predefined plan files of the Smart Draw software.
- •20 old musical scores from a collection of modern and old musical scores (19th century) of the Archive of the Seminar of Barcelona.
- •70 object categories from the public MPEG7 binary object data set.





CBSM	BSM	Zernique
71.84 (6.73)	65.79 (8.03)	43.64 (7.66)
Zoning	CSS	SIFT
58.64 (10.97)	37.01 (10.76)	29.14 (5.68)

3. CONCLUSIONS

We presented the Circular Blurred Shape Model descriptor. The descriptor codifies the spatial arrangement of object parts based on a prior blurring degree. The descriptor has shown to be potentially useful to describe objects that may suffer from irregular deformations, such as the symbols that appear in document analysis. The descriptor is learnt using a cascade of classifiers with Adaboost to discard non-object regions, and tested over whole images, localizing the target objects. The symbol spotting procedure presented in this paper shown to robustly locate object instances in documents, such as symbols in plans and old musical scores. Moreover, the presented descriptor also outperforms the state-of-the-art descriptors when compared in multi-class object categorization problems.