Multi-class Binary Symbol Recognition with Circular Blurred Shape Models

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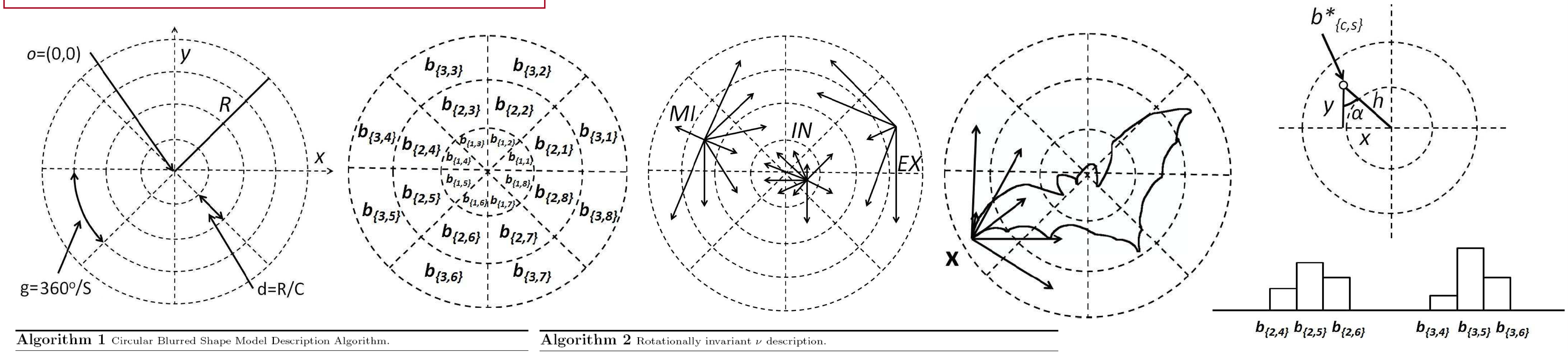
ABSTRACT

Multi-class binary symbol classification requires the use of rich descriptors and robust classifiers. *Shape representation is a diffcult* task because of several symbol distortions, such as occlusions, elastic deformations, gaps or noise. In this paper, we present the Circular Blurred Shape Model descriptor. This descriptor encodes the arrangement information of object parts in a correlogram structure. A prior blurring degree defines the level of distortion allowed to the symbol. Moreover, we learn the new feature space using a set of Adaboost classifiers, which are combined in the Error-Correcting Output Codes framework to deal with the multi-class categorization problem. The presented work has been validated over different multi-class data sets, and compared to the state-o-the-art descriptors, showing significant performance improvements.

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:
$L_G = \sum_{j,k} \nu(b_{\{j,k\}}), j \in [1, .., C], k \in [i+1, .., i+S/2-1]$
$R_G = \sum_{j,k} \nu(b_{\{j,k\}}), j \in [1, .., C], k \in [i+S/2+1, .., i+S-1]$

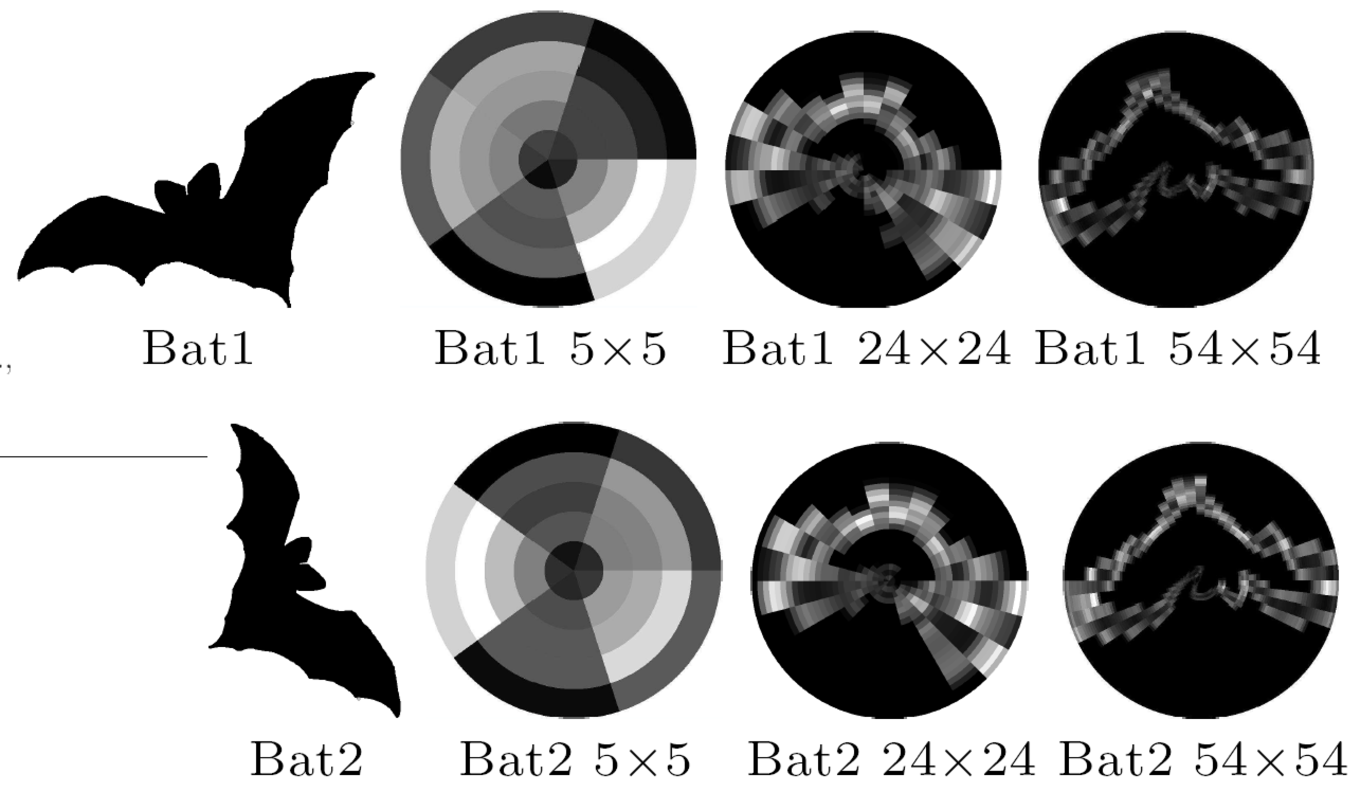
if $L_G > R_G$ **then**

  B is rotated $k = i + S/2 - 1$ positions to the left:
  $\nu^{ROT} = \{\nu(b_{\{1,k+1\}}), .., \nu(b_{\{1,S\}}), \nu(b_{\{1,1\}}), .., \nu(b_{\{1,k\}}), .., , .., \nu(b_{\{C,k+1\}}), .., \nu(b_{\{C,S\}}), \nu(b_{\{C,1\}}), .., \nu(b_{\{C,k\}})\}$

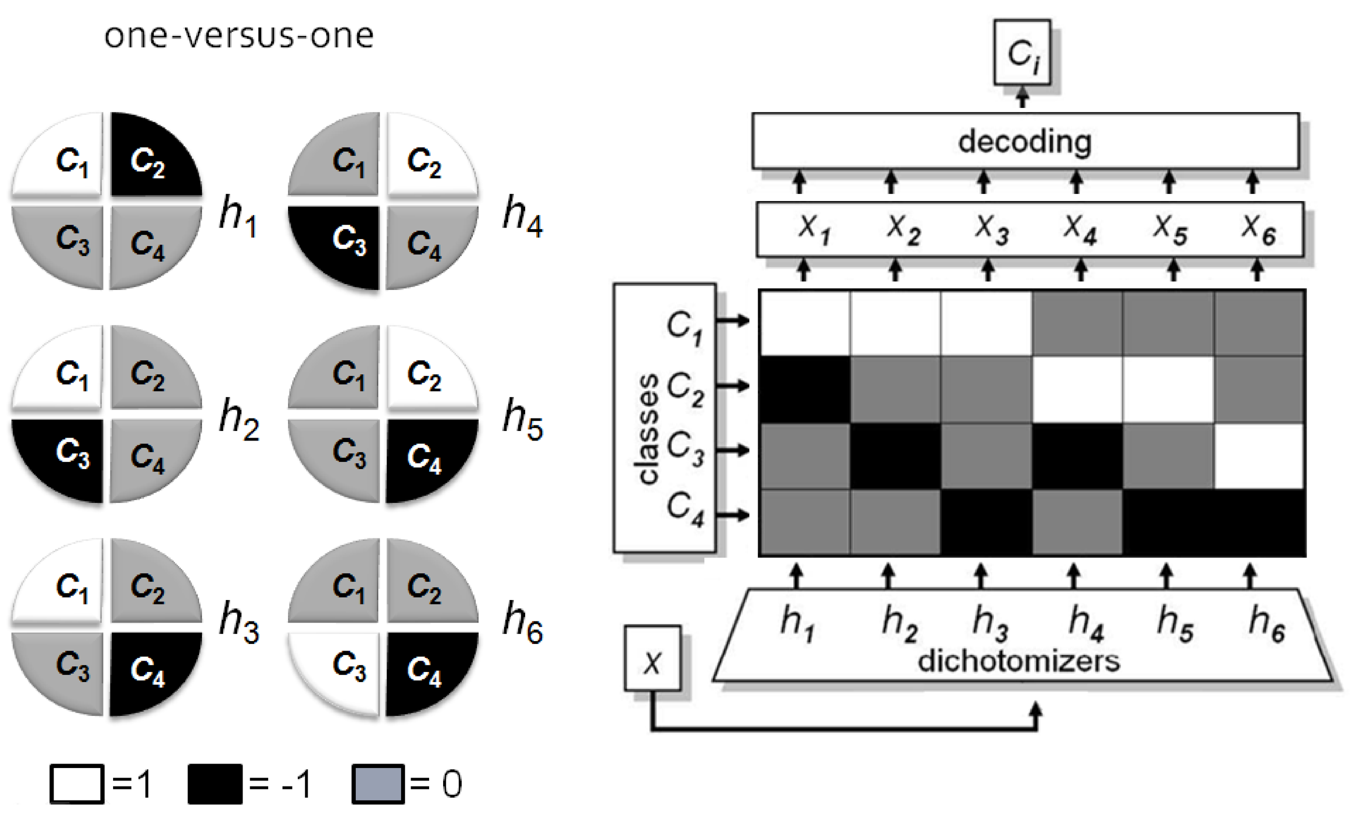
else

  B is rotated $k = i - 1$ positions to the right:
  $\nu^{ROT} = \{\nu(b_{\{1,S\}}), .., \nu(b_{\{1,S-k+1\}}), \nu(b_{\{1,1\}}), .., \nu(b_{\{1,S-k\}}), .., , .., \nu(b_{\{C,S\}}), .., \nu(b_{\{C,S-k+1\}}), \nu(b_{\{C,1\}}), .., \nu(b_{\{C,S-k\}})\}$

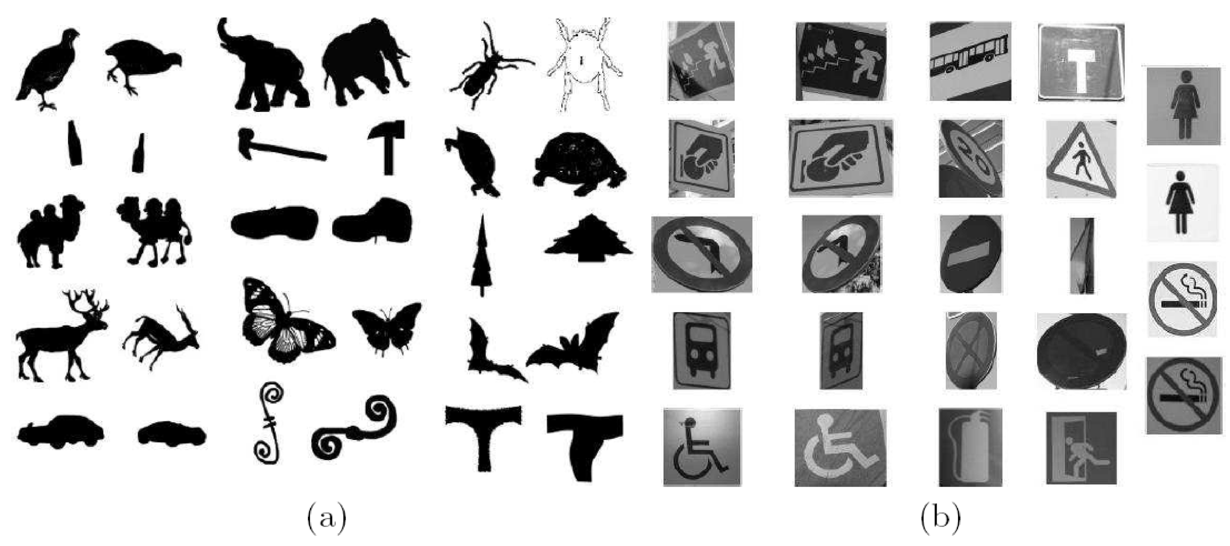
end if



2.ERROR-CORRECTING OUTPUT CODES



3.RESULTS



(a) (b)

(a) MPEG samples, and (b) Grey-scale symbol data set samples.

Descriptor	3*NN*	ECOC Adaboost
CBSM	**71.84(6.73)**	**80.36(7.01)**
BSM	65.79(8.03)	77.93(7.25)
Zernique	43.64(7.66)	51.29(5.48)
Zoning	58.64(10.97)	65.50(6.64)
CSS	37.01(10.76)	44.54(7.11)
SIFT	29.14(5.68)	32.57(4.04)

CBSM	SIFT
77.82(6.45)	62.12(9.08)

4. CONCLUSIONS

In this paper, we presented the Circular Blurred Shape Model descriptor. The new descriptor is suitable to describe and recognize symbols that can suffer from several distortions, such as occlusions, rigid or elastic deformations, gaps or noise. The descriptor encodes the spatial arrangement of symbol characteristics using a correlogram structure. A prior blurring degree defines the level of degradation allowed to the symbol. Moreover, the descriptor correlogram is rotated guided by the major density so that it becomes rotationally invariant. The new symbol descriptions are learnt using Adaboost binary classifiers, and embedded in an Error-Correcting Output Codes framework to deal with multi-class categorization problems. The results over different multi-class categorization problems and comparing with the state-of-the-art descriptors show higher performance of the present methodology when classifying high number of symbol classes that suffer from irregular deformations.