Shape Matching Using Points Co-Occurrence Pattern

Yu Zhou, Junwei Wang, Quan Zhou, Xiang Bai, Wenyu Liu
Department of Electronics and Information Engineering
Huazhong University of Science and Technology
Wuhan, 430074, P.R.China
Email: zhouyu.hust@gmail.com

***Abstract*—Shape matching is a very critical problem in computer vision, and many smart features have been designed in recent literature for improving the similarity measure between pairs of shapes, and most of them consider either distribution of the sample contour points, or convexity/concavity property of the contour. In this paper, we design a novel shape feature to capture the Co-Occurrence Pattern (COP) of the points sampled from any given shape contour, and each pattern is described by Self-Similarity which investigates the spatial co-occurrence relation among all the sample points. We test our feature on three famous shape databases: MPEG-7 CE-Shape-1 part B, Tari1000, and Kimia99 data set for shape matching and retrieval. The experimental results show that the proposed descriptor achieves higher computational efficiency with no significant performance loss.**

***Keywords*-Shape matching; Co-occurrence Pattern; Self-Similarity; Dimension reduction.**

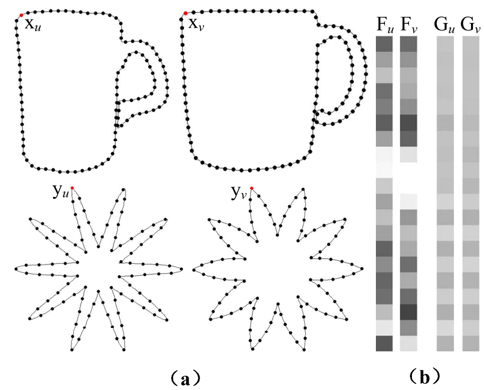

Figure 1. Examples of Point Co-Occurrence Pattern and Self-Similarity descriptor.

I. Introduction

Shape matching is a very important issue and challenging task in computer vision. It requires the shape descriptor is powerful enough to represent original shape and discriminative enough to distinguish two shapes form different categories. A good shape descriptor can not only fight against the geometric transformation such as rotation, translation and scale variance, but also handle intra-class variance for two shapes in the same category with articulation and deformation. Although many smart features [3], [4], [1], [14], [2] have been proposed for shape matching and retrieval, how to design an effective and representative shape descriptor remains unsolved.

In this paper, we present a novel shape descriptor, called Co-Occurrence Pattern (COP), to facilitate the computational efficiency and improve the matching performance. In Fig. 1(a), we illustrate two shapes (*cup* and *star*) represented by sample points and (b) show the COP descriptor for points x_u, x_v, y_u and y_v, respectively. More specifically, the original shape is described by a serious of sample points with equal distance on shape contour and each sample point is described by shape context [1]. To further characterize the shape contour, we use the Self-Similarity (SS) [21], [19], [15], [22] to measure the co-concurrence distance between arbitrary pair of sample points. Then we divide all shape contour into several contours segments and the COP of each sample point is described by SS between this sample point and these segments. Finally, we use the dynamic programming (DP) [2] algorithm to perform matching between two shapes.

The remainder of this paper is organized as follows. Immediately below, we compare our feature and some current shape descriptors in the literature. Section II entails the computational process to obtain the COP and presents the matching algorithm based on COP. Section III gives the qualitative and quantitative experimental results by applying COP in shape matching and the whole paper concludes with a summary in Section IV.

A. Literature Review

Many features have been designed for shape matching and they are largely divided into three categories. The first category uses the spatial distribution to encode local information of shape contour. The typical approach is shape context [1], which utilizes the geometric relationship between contour sample points. The feature [2] proposed by H. Ling, called inner distance shape context, extends the shape context to further explore the length of the shortest path between landmark points within the shape silhouette.

The second category of shape descriptors investigates the characteristic of contour convexity/concavity [4], [13], [14]. In [4], the author presents a triangle area measurement to describe each point using the signed areas of triangles formed

978-0-7695-4541-7/11 $26.00 © 2011 IEEE
DOI 10.1109/ICIG.2011.103

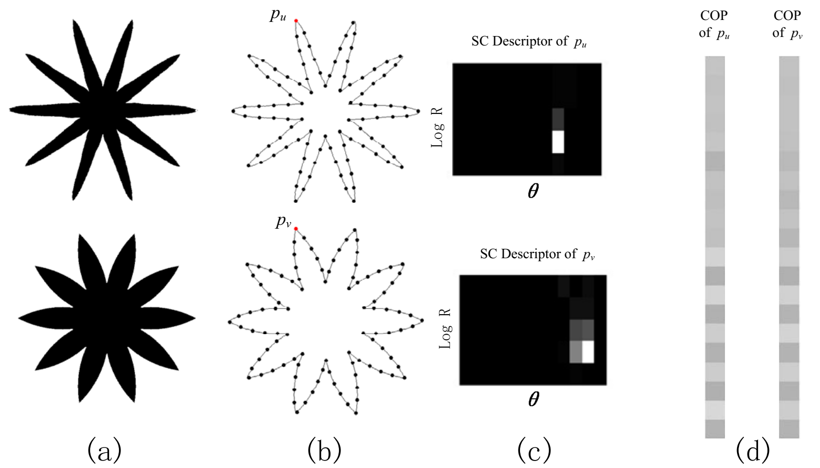

Figure 2. (a) Original binary shapes, (b) shape contours with sample points, (c) shape context descriptors, (d) COP.

by boundary points at different scales. This representation is effective in capturing both local and global shape characteristics. Shapes can also be decomposed into perceptually meaningful parts by digital curve evolution (DCE) [13], and the matching is performed based on these parts. Another feature to combine local and global information is to us hierarchy structure [14].

The final category mainly focuses on the topology information for given object shape. One effective feature to describe shape topology is the skeleton abstracted from original binary shape. In [8], the shape contour is represented by a serious of skeleton branches, then each point in the skeleton branches is encoded by the radius of minimum inscribed circle. The skeleton is unaffected by geometric transformation and is able to effectively handle the intra-class variance, such as articulation and deformation.

Despite their success, these methods only represent object shapes through the local and global information by different aspects of shape characteristics. When the object has large variations or exhibits large inter-class similarities, they are inefficient in expressing shape information. In addition, the high dimension of these features results in expensive computational cost in matching process. Compared with these features mentioned above, our COP descriptor has the following characteristics:

(1) The COP is the extension of local and global feature to capture shape information. COP computes the co-occurrence distance between two sample points which effectively investigate the local information of original shapes. By calculating distance among all sample points, the COP is representative for describing global shape. Thus COP can be considered as some kind of "meta descriptor" for shapes.
(2) The COP is more powerful and discriminative to represent shapes. It measures the similarity or dissimilarity between two sample points, which is invariant to geometric transformation and intra-class deformation. Moreover, COP is able to inherit the properties of primary descriptors for sample points. For example, if we adopt the primary descriptor as shape context, the COP automatically obtain the properties of shape context.
(3) Using the SS to compute COP is efficiently to reduce the feature dimension which results in the release of computational burden for shape matching.

II. Shape Matching with Point Co-Occurrence Pattern

In this section, we first elaborately introduce how to compute the COP feature and then present the matching algorithm based on abstracted COP.

A. Point Co-Occurrence Pattern

Following many recent shape description methods, we treat the object (the shape contour) as a finite point set. As shown in Fig. 2(b), given a binary shape $\mathcal{S}$ and its corresponding shape contour $\mathcal{C}$, we uniformly sample N points, denoted as $\{p_i \subset \mathcal{C}, i = 1, ..., N\}$. For the sampled point p_u, the Shape Context descriptor is defined as:

$$h_{p_u} = \#\{q \neq p_u : (q - p_u) \in bin(k)\} \quad (1)$$

where q is the remaining $N-1$ points in $\mathcal{C}$ and k denotes the k^{th} bin number of a log-polar histogram h_{p_u}. In Fig. 2(c), we exhibit two shape context features for p_u and p_v abstracted from two shapes of flower, indexed by orientation θ and distance $\log R$.

With the shape context feature h_{p_u} in hand, we define COP for point p_u using Self-Similarity, which measures the similarity between p_u and the remaining sample points. Since h_{p_u} encodes the statistic location information of sample points with respect to p_u, χ^2 distance is adopted to measure the difference among two histogram distributions:

$$s_{u,u'} \equiv s(p_u, p_{u'}) = \frac{1}{2}\sum_{k=1}^{K}\frac{[h_u(k) - h_{u'}(k)]^2}{h_u(k) + h_{u'}(k)} \quad (2)$$

where $s_{u,u'}$ denotes the self-similarity value for sample points p_u and p'_u. We collect all self-similarity distance from N sampled points and the feature for p_u is an N dimensional vector.

$$S_u = (s_{u,1}, s_{u,2}, ..., s_{u,n-1}, s_{u,N})^T. \quad (3)$$

Accroding to Eqn(3), the increase of sample point number N will result in the heavy computational cost, which may make the matching intractable. The intuitive idea to handle this problem is to perform dimension reduction such as PCA [23]. However, directly using the PCA will reduce the descriptive ability to original shape. In order to effectively maintain the contour information, we adopt a local-global transformation to perform dimension reduction. We separate the original shape into M fragments and each fragment contains $K = \frac{N}{M}$ sample points. Correspondingly, S_u is also split into M components and the self-similarity value of the k^{th} point in the m^{th} component is denoted by $s^m_{u,k}$, then the final COP feature for the sample point p_u is

$$R_u = (d^1_u, d^2_u, ..., d^M_u)^T. \quad (4)$$

where $d^m_u = \frac{1}{K}\sum_{k=1}^{K} s^m_{u,k}$. In Fig. 2(d), we illustrated the final feature after dimension reduction and we observe that although p_u and p_v come from two different shapes, they have very similar COP feature since they belongs to the same category.

Based on Eqn(3) and Eqn(4), each shape can be represented by a COP matrix, denoted as $\mathcal{R}_{M\times N}$, where each column R_u $(u = 1, ..., N)$ is the COP feature calculated for the u^{th} sample point. To achieve balance contribution, the elements in each row are divided by the maximum value of this row:

$$r_{m,n} = \frac{r_{m,n}}{\max_{n=1,...,N}\{r_{m,n}\}}. \quad (5)$$

In the next subsection, we introduce the matching algorithm by given the COP matrices of two shapes.

B. Shape Matching using Dynamic Programming

The problem of shape matching can be transferred into the task of sequence alignment by matching the sample points based on shape descriptors. When solving the sequence alignment problem, we use the Dynamic Programming (DP) [3], [4], [2] method.

Consider sample point p and q from two different shapes. We naturally define the matching cost of such two points using the feature distance between the COP descriptors, denoted as $C(p, q)$. In our method, the L_1 norm is used to measure the COP descriptor. Then the matching cost of p and q is:

$$C(p, q) = \sum_{m=1}^{M}\omega_m|r_{p,m} - r_{q,m}|, \quad (6)$$

where ω_m is the weight coefficient for every component of the COP feature. The bigger $C(p, q)$ is, the less similar p and q are.

To satisfy both of the requirements of point correspondence and misalignment punishment, the partial optimal alignment score is evaluated by the following formula when filling the score matrix:

$$D(p, q) = C(p, q) + min\begin{cases} D_p(p-1, q) + \lambda \\ D_p(p-1, q-1) \\ D_p(p, q-1) + \lambda \end{cases} \quad (7)$$

where $D(p, q)$ is the total distance between the two subsequences with end points p and q that come from two different shapes; $D_p(p-1, q)$, $D_p(p-1, q-1)$ and $D_p(p, q-1)$ denote the total distances for the left, up-left and up predecessors in the score matrix respectively, and λ is the penalty factor to punish misalignments.

The overall shape similarity is affected and determined not only by the feature distances between corresponding points but also by the situations of point alignments. The corresponding matching result is a tradeoff between similar point correspondence and good point alignments. The penalty factor λ influences the importance or weights of the two factors when calculating shape similarity, thus should be adjusted to a proper value.

Since the starting points for both shape contours are in fact unknown, it is necessary to investigate all possible starting points. This means that DP algorithm must be repeated N times. The whole shape matching algorithm using COP is shown in Algorithm 1.

III. EXPERIMENTS

This section gives the experimental results using our method. We test the effect of the proposed method with three widely used shape databases, i.e., MPEG-7 data set [16], Tari1000 data set [5] and Kimia's 99 data set [6].

A. MPEG-7 Shape Database

The database of MPEG-7 CE-Shape-1 part B [16] is very famous in shape matching and classification. This database consists of 1400 binary images from 70 shape categories, i.e., 20 images per category. This data set is difficult since there are some large intra-class variances. Examples of this

Algorithm 1: Shape Matching Algorithm Based on Co-Occurrence Pattern(COP)

Input: A pair of binary shapes S_1, S_2

Output: Shape distance between S_1 and S_2

1 Extract shape contour C_1 and C_2 for S_1 and S_2, and uniformly sample C_1 and C_2 with N points respectively, for $S_1 : \{p_i \subset C_1, i = 1, ..., N\}$, for $S_2 : \{q_j \subset C_2, j = 1, ..., N\}$.

2 Calculate shape context descriptor for $p_i(i = 1, ..., N)$ and $q_j(j = 1, ..., N)$ respectively based on Eqn(1).

3 Calculate self-similarity descriptor for $p_i(i = 1, ..., N)$ and $q_j(j = 1, ..., N)$ respectively based on Eqn(2).

4 Reduce feature dimension for $p_i(i = 1, ..., N)$ and $q_j(j = 1, ..., N)$ respectively based on Eqn(4).

5 Calculate matching cost between $p_i(i = 1, ..., n)$ and $q_j(j = 1, ..., N)$ based on Eqn(6).

6 Matching $p_i(i = 1...N)$ and $q_j(j = 1, ..., N)$ based on Eqn(7).

data set are given in Figure 3. Following the common performance measurement "bulls-eye test" [3][2][4][1], we treat every image in this database as a query, and count the number of correct images in the top 40 matches. For MPEG-7, the values of the parameters are set as $k = 5$ and $\lambda = 0.0$.

Figure 3. Example shapes in MPEG-7 CE-Shape-1 part B database.

Table I presents the retrieval rates of our method and some classical descriptors, along with their feature dimensions. We see that our method achieves a considerable retrieval rate (only lower than Triangle Area [4]) with smaller dimension. The dimensions of Shape Context and Inner-Distance Shape Context is 60 and 96, referring to 12 angle bins and 5 or 8 distance bins, respectively.

Table I

RETRIEVAL RATES (BULLSEYE) OF DIFFERENT METHODS FOR THE MPEG-7 CE-SHAPE-1 PART B ALONG WITH THE DIMENSIONS OF THE SHAPE FEATURES

Algorithm	Score	Dimention
SC+SS+DP(Ours)	**86.80%**	**20**
TAR [4]	87.13%	63
SC+DP [17]	86.80%	96
IDSC+DP [2]	85.40%	96
Generative Models [18]	80.03%	-
SC+TPS [1]	76.51%	60

A more careful comparison between our method and Shape Context is given by Figure 4, which shows the retrieval rates of the two methods for every category in MPEG-7 data set. The shape matching algorithm for the two methods are both DP.

B. Tari1000 Database

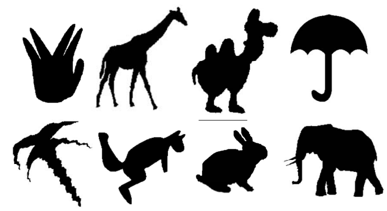

Figure 5. Example Shapes in Tari1000 database.

Tari1000 [5] is also a large database for binary images. It consists of 1000 binary images from 50 shape categories, i.e., 20 images per category (the same as MPEG-7). Some of these categories are also included in the MPEG-7 database, such as *brick*, *cattle*, *cellular*, *phone*,*face*, *flatfish*, *fountain*, *key*,*ray*, *teddy*, *watch* and so on. Figure 5 gives some examples for this data set. When testing the retrieval performance, we follow two rules, one is the "bulls-eye test", and the other is precision-recall curve. For this data set, the values of the parameters are set as $k = 4$ and $\lambda = 0.0$.

When following the "bulls-eye test", the score of our method is 92.18%, comparable with the result of Shape Context, which is 94.18% [17]. Figure 6 shows the Precision-Recall curves of our method along with other methods. Our method is slightly weaker than Shape Context, but significantly outperforms the methods in [5].

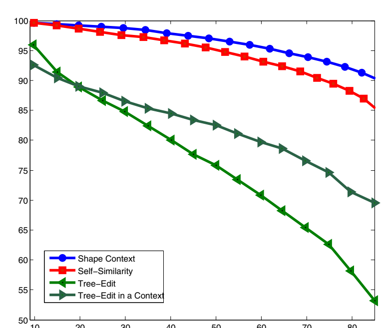

Figure 6. Precision/Recall curves on Tari1000 database

C. Kimia's 99 Database

The Kimia's 99 shape data set is also very famous in shape matching and recognition. This data set [6] includes ninety nine binary images from nine categories (see in Fig. 7). The retrieval result is summarized by counting the correct number of top 1 to top 10 nearest matches. The best possible

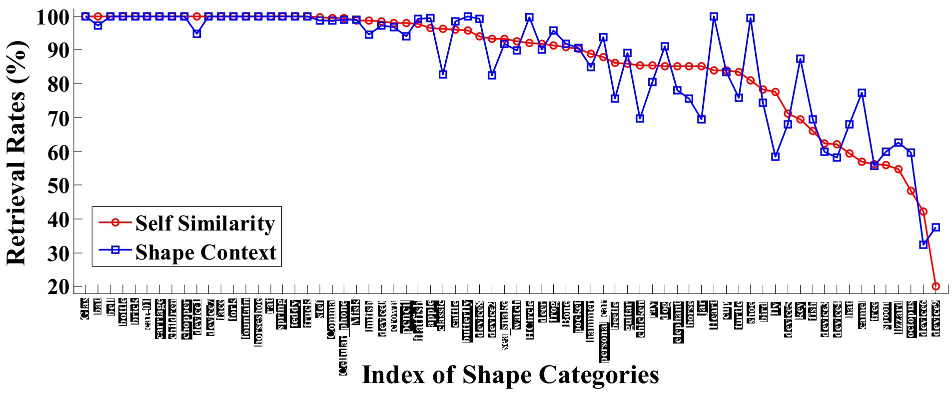

Figure 4. Comparison of our method and Shape Context in MPEG-7 CE-Shape-1 part B database.

Table II
RETRIEVAL RESULTS ON KIMIA'S 99 DATA SET [6]

Algorithm	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	dimension
SC+TPS [1]	97	91	88	85	84	77	75	66	56	37	96
Gen. Model [18]	99	97	99	98	96	96	94	83	75	48	-
IDSC+DP [2]	99	99	99	98	98	97	97	98	94	79	96
Triangle Area [4]	99	99	99	98	98	97	98	95	93	80	63
SC+SS+DP	**99**	**99**	**99**	**98**	**95**	**94**	**94**	**96**	**77**	**59**	**20**

Figure 7. Example Shapes in Kimia's 99 database.

result for each of them is 99. For this data set, the values of the parameters are set as $k = 5$ and $\lambda = 0.0$.

Table II gives the results of our method and some recent descriptors. Our method outperforms Shape Context and Generative Model, and is comparable with IDSC and Triangle Area except for the last two numbers.

IV. CONCLUSION

Most of recent shape descriptors focused on the properties of intrinsic curve or sample points. In this paper, a novel shape feature to capture the Co-Occurrence Pattern (COP) of the sample points is proposed, and each pattern is described by the Self-Similarity descriptor. As one kind of "meta descriptor" for shape matching, the proposed COP feature inherits all good properties from the original descriptor, and it is more robust to fight against local shape deformations. In addition to its discriminative power, the given descriptor is also preferable for shape matching and retrieval task for large databases due to its small feature dimension. Retrieval experiments on some benchmarks such as MPEG-7, Tari1000, and Kimia's 99 data sets show that even with a much lower dimension, the new feature is still quite informative for shape matching and retrieval.

ACKNOWLEDGMENT

The authors would like to thank Ling and Jacobs for releasing their source code of IDSC online. Parts of our work are accomplished by directly using corresponding parts of this code or slightly modifying them. This work was supported by National Natural Science Foundation of China #60903172, #60903096 and #60873127.

REFERENCES

[1] Serge Belongie, Jitendra Malik and Jan Puzicha, Shape matching and object recognition using shape context, *IEEE Trans. on Pattern Analysis and Machine Intelligence (TPAMI)*, 2002, 24, 509-522, April.

[2] Haibin Ling and David W. Jacobs, Shape classification using Inner-Distance, *IEEE Trans. on Pattern Analysis and Machine Intelligence (TPAMI)*, 2007, 29, 286-299, February.

[3] Tomasz Adamek and Noel E. O'Connor, A multiscale representation method for nonrigid shapes with a single closed contour. *IEEE Trans. on Circuits and Systems for Video Technology (TCSVT)*, 2004, 14, 742-753, May.

[4] N. Alajlan, M. Kamel and G. Freeman, Geometry-based image retrieval in binary image databases. *IEEE Trans. on Pattern Analysis and Machine Intelligence (TPAMI)*, 2008, 30, 1003-1013, June.

[5] E. Baseski, A.Erdem and S. Tari, Dissimilarity between two skeletal trees in a context. *Pattern Recognition (PR)*, 2009, 42, 370-385, March.

[6] Thomas B. Sebastian, Philip N. Klein and Benjamin B. Kimia, Recognition of shapes by editing their shock graphs. *IEEE Trans. on Pattern Analysis and Machine Intelligence (TPAMI)*, 2004, 25, 116–125, February.

[7] Xiang Bai, Longin Jan Latecki and Wenyu Liu, Skeleton pruning by contour partitioning with discrete curve evolution, *IEEE Trans. on Pattern Analysis and Machine Intelligence (TPAMI)*, 2007, 29, 449-462, March.

[8] Xiang Bai and Longin Jan Latecki, Path similarity skeleton graph matching, *IEEE Trans. on Pattern Analysis and Machine Intelligence (TPAMI)*, 2008, 30, 1282-1292, July.

[9] Xiang Bai, Xingwei Yang, Longin Jan Latecki, Wenyu Liu and Zhuowen Tu, Learning context sensitive shape similarity by graph transduction, *IEEE Trans. on Pattern Analysis and Machine Intelligence (TPAMI)*, 2010, 32, 861-874, May.

[10] Hairong Liu, Longin Jan Latecki and Wenyu Liu, A unified curvature definition for regular, polygonal, and digital planar curves, *International Journal of Computer Vision (IJCV)*, 2008, 80, 104-124.

[11] Wei Shen, Xiang Bai, Rong Hu, Hongyuan Wang and Longin Jan Latecki, Skeleton growing and pruning with bending potential ratio, *Pattern Recognition (PR)*, 2010, 44, 196-209, Feb.

[12] Zhuowen Tu, Songfeng Zheng and Alan Yuille, Shape matching and registration by data-driven EM, *Computer Vision and Image Understanding (CVIU)*, 2008, 109, 290-304, Mar.

[13] Longin Jan Latecki and Rolf Lakamper, Shape similarity measure based on correspondence of visual parts, *IEEE Trans. on Pattern Analysis and Machine Intelligence (TPAMI)*, 2000, 22, 1185-1190, October.

[14] Pedro F. Felzenszwalb and Joshua D. Schwartz, Hierarchical matching of deformable shapes", *IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2007.

[15] Eli Shechman and Michal Irani, Matching local self-similarities across image and video", *IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2007.

[16] Longin Jan Latecki, Rolf Lakamper and Ulrich Eckhardt, Shape descriptors for non-rigid shapes with a single closed contour, *IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2000.

[17] Xiang Bai, Bo Wang, Xinggang Wang, Wenyu Liu and Zhuowen Tu, Co-transduction for shape retrieval, *European Conf. on Computer Vision (ECCV)*, 2010.

[18] Zhuowen Tu and A.L. Yuille, Shape matching and recognition using generative models and informative features, *European Conf. on Computer Vision (ECCV)*, 2004.

[19] T. Deselaers and V. Ferrari, Global and efficient self-Similarity for object classification and detection", *IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2010.

[20] Hairong Liu, Longin Jan Latecki, Wenyu Liu and Xiang Bai, Visual curvature, *IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2007.

[21] K. Chatfield, J. Philbin and A. Zisserman, Efficient retrieval of deformable shape classes using local self-similarities, *In NORDIA Workshop at International Conf. on Computer Vision (ICCV)*, 2009.

[22] P. Viola and W.W. III, Alignment by maximization of mutual information, *In International Conf. on Computer Vision (ICCV)*, 1995.

[23] Richard O. Duda, Peter E. Hart and David G. Stork, Pattern classification (2nd ed), *Wiley-Interscience*, 2000.