Organic Shapes Classification by Similarity to Basic Geometric Shapes

Saulius Sinkevicius, Arunas Lipnickas and Kestas Rimkus
Department of Automatics
Kaunas University of Technology
Kaunas, Lithuania
saulsink {at} gmail.com

***Abstract*— This paper proposes and describes a novel technique for organic shapes classification by similarity to basic geometric shapes. The amber data used in experiments are collected by amber art craft industry experts and the presented investigations were care out in order to develop a classifier for online amber sorting application. The centroid distance function was selected for shape representation as it preserves the order of landmark points. The k-medoids and k-means clustering algorithms were compared by generating clusters of similar shapes for labeling to one of geometric shapes: circle, ellipse, oval, triangle, rectangle, rhombus, trapezium, and trapezoid. Clusters labeled by an expert to same categories were merged. Using labeled samples the decision tree classifier was trained. The training of classifier was made by acquiring all possible orientations of centroid distance function for each image in training set and then feeding them to decision tree. In the classification step all the shifted and flipped centroid distance function variations of the testing sample are voting for the class using the decision tree. Experimental results have shown that the proposed technique is effective in organic shapes classification to selected geometric shapes even if there is high ambiguity between organic shapes.**

Keywords-Expert systems, image classification, image matching, pattern clustering.

I. INTRODUCTION

Baltic amber gemstones are still mined in present time and used as decorative component for jeweler, souvenirs, or art paintings. The smallest pieces of amber, combining their color tones, transparency, variegation, shape and other interface features is mostly used by art crafters. At this time sorting of amber pieces according to the similarity to geometric shapes is complicated and time consuming process, manly performed by "the eye of human being". The presorted gemstones may be further used for automated craft making. The best solution for amber classification by similarity to geometric shapes is the implementation of fully automated industrial sorting line based on machine vision.

Many researchers have been published promising results on shape classification: a shape descriptor based on inner-distance is robust to articulation and capture part structure [1]; the authors in [2] used correspondence-based technique on the MPEG7 CE-Shape-1 database for efficient shape classification and retrieval, outperforming the popular contour Fourier method [3]; a framework [4] was developed to recognize objects in images based on their silhouettes; a contour-based shape descriptor presented in [5] avoids the time-consuming pairwise matching encountered in most of the previously used shape recognition algorithms; an image retrieval method proposed in [6] has better performance than the classical methods based on interest points; an interesting image analysis technique [7] that allows a rapid classification of the types of vehicles observed from the side view is the shape analysis.

However although many methods for shape representation have been proposed [8], little work has been reported on classification to geometric shapes and how closely these measures match human perceptions of geometric similarity [9]. Although there are attempts to classify shapes to geometric shapes [10]-[11]-[12]-[13]-[14]-[15], but most of those methods have limits in sense of choosing to which geometric shapes to classify, sensitivity to minor dissimilarities, and time-consuming pairwise matching.

Our proposed approach overcomes mentioned limits and is able to classify objects to selected geometric shapes even if most shapes are irregular and very similar to each other. Although an expert knowledge should be involved. The method is invariant to translation, rotation, scaling, and reflection.

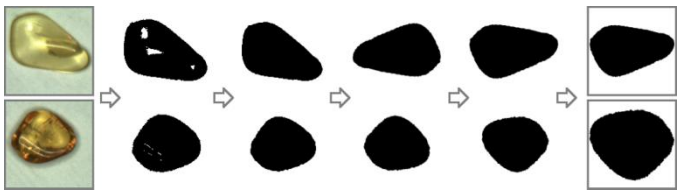
The paper contains four main sections. In the second Section, theoretical background is overviewed. The third Section gives more information about used data and the experimental results. Finally, conclusions are given in Section IV.

II. METHODS

The approach suggested involves image normalization, clustering, and classification techniques. The system automatically processes images and prepares clusters for labeling. Instead of labeling individual samples, clusters are labeled by an expert as similar to geometric shape like triangle or rectangle. The new samples are classified using clusters labeled by an expert.

A. *Image preprocessing*

The process of image normalization is shown in Fig. 1. First step consist of image conversion from RGB color space to binary image (Fig. 1. b). The threshold for conversion is selected using Otsu's method [16].



a) b) c) d) e) f)

Figure 1. Two examples of image normalization: (a) camera view; (b) binary image; (c) holes filled and shadows dilated; (d) aligned to abscissa axis; (e) centroid is below x axis; (f) width resized and height padded with zeros.

Holes are filled and shadows around the object are removed with morphological dilation operation (Fig. 1. c). If the shape is cut by camera view limits, such shape is removed from database. The scale is normalized by aligning image by its longest part to abscissa axis (Fig. 1. d). If centroid of image is above the axis, then the image is rotated by 180 degrees (Fig. 1. e). In final step, width of the image is resized to 256 pixels keeping aspect ratio to height and the height padded to 256 pixels with zeros (Fig. 1. f). The preprocessed image is preceded for shape analysis.

B. *Shape Signature*

As a shape signature a centroid distance function (CDF) was selected. It is one-dimensional $\mathrm{r}(n)$ function expressed by the distance of the landmark points from the centroid (g_x, g_y) of a shape [8]:

$$\mathrm{r}(n) = \left((\mathrm{x}(n) - g_x)^2 + (\mathrm{y}(n) - g_y)^2\right)^{1/2}, \quad (1)$$

where the coordinates of landmark points are calculated implementing the Moore-Neighbor tracing algorithm modified by Jacob's stopping criteria [17] - $\mathrm{P}(n) = (\mathrm{x}(n), \mathrm{y}(n))$, $n \in [1, N]$, N - the number of landmark points. The number of boundary points given by Moore-Neighbor tracing algorithm for every shape is different and should be normalized to selected constant - N. This can be applied simply by uniformly selecting desired number of points by averaging points in between or adapting more sophisticated approximation technique. As a result, the number of landmarks for every shape is the same - N.

C. *Clustering*

Two clustering methods were compared. *k*-medoids [21] algorithm is partitional (breaks the dataset up into groups) and attempts to minimize the distance between points labeled to be in a cluster and a point designated as the center of that cluster. *k*-medoids uses most centrally located objects (medoids) in a cluster instead of taking the mean value of the objects in the cluster as *k*-means [21] algorithm do. This means that the *k*-medoids accepts a dissimilarity matrix as input while the *k*-means accepts a matrix of features.

The dissimilarity matrix for *k*-medoids was computed by measuring similarity between CDF functions. Each CDF value is divided by the sum of all distances in the CDF function:

$$\mathrm{r}'(n) = \mathrm{r}(n)\left(\sum_{i=1}^{N} \mathrm{r}(i)\right)^{-1}, \quad (2)$$

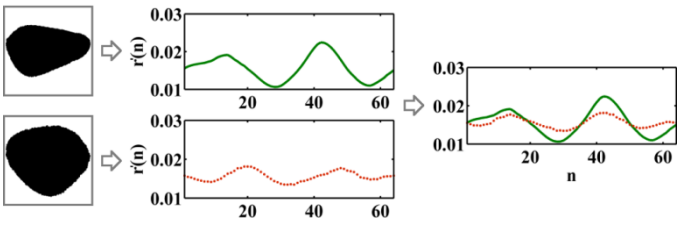
Shape representation $\mathrm{r}'(n)$ is invariant to translation due to the subtraction of centroid from landmark coordinates. In order to compensate for orientation changes, shift matching is needed to find the best matching between two shapes:

$$m = 1 - \min_{i \in \{0,\ldots,N/S-1\}} \left(\sum_{j=1}^{N} \left| \mathrm{r}_1'(j) - \mathrm{r}_2'(\mathrm{I}(i,j)) \right| \right) \quad (3)$$

$$\mathrm{I}(i,j) = \begin{cases} iS + j, & iS + j \le N \\ j + iS - N, & iS + j > N \end{cases} \quad (4)$$

where m - similarity value between two shapes (higher values means higher similarity), S - denotes the number of different starting points for alignment uniformly chosen from landmark points.

Matching will be invariant to reflection if the CDF vector is flipped - $\mathrm{r}_2''(n) = \mathrm{r}_2'(N - n + 1)$ and then flipped version of CDF $\mathrm{r}_2''(n)$ is matched to $\mathrm{r}_1'(n)$. The maximal similarity value of matching $\mathrm{r}_1'(n)$ with $\mathrm{r}_2'(n)$ and $\mathrm{r}_1'(n)$ with $\mathrm{r}_2''(n)$ will be the final value representing similarity between two shapes. It is invariant to translation, rotation, scaling, and reflection (Fig. 2). By doing pairwise matching the dissimilarity matrix for *k*-medoids was acquired.



a) b) c)

Figure 2. Example of CDF extraction and matching: (a) normalized images; (b) CDF representations of images; (c) matching by minimal distance; the CDF of image below was flipped and shifted by 5 points to the left to get best matching position.

The features matrix for *k*-means was computed in two steps. In first step, S number of CDF functions from each sample was extracted with different starting point and the same number of flipped variations, so $2S$ CDF functions per sample in total. All extracted CDF functions from training set were clustered by *k*-means in predefined set of C clusters. As a result, each variation of CDF function in training set was assigned to one of C clusters by *k*-means. In second step, the

C length feature vector for each sample in training set was computed by summarizing all its $2S$ CDF functions. The feature matrix was made from all samples and further used by *k*-means. Final clusters were formed by k-means using this features matrix.

For clustering validation we used two clustering validity indices, and they both accept similarity matrix as input. Those validity indices are more a guide for an expert to pick optimal number of clusters than a method to do it automatically. Dunn's Validity Index [19] attempts to identify those cluster sets that are compact and well separated. Large values of the index indicate the presence of compact and well-separated clusters. The silhouette value [20] for each point is a measure of how similar that point is to points in its own cluster compared to points in other clusters. This technique computes the silhouette width for each data point, average silhouette width for each cluster and overall average silhouette width for the total data set.

D. *Classification*

For classification a decision tree (DT) [22] was created. The DT is trained using a features matrix where rows are the feature vectors. One observation has $2S$ feature vectors because of CDF function variations. The constructed DT model is able to evaluate one CDF predicting its membership class.

In testing phase the classification itself for one sample is done by evaluating all $2S$ CDF function variations using DT and then all $2S$ variations votes by majority rule. The winner class is assigned to the sample.

For the method validation the public databases with known labels are used. The validation is done by using *10*-fold cross validation [18]. One tenth of data is used for validation and the remaining samples as the training data.

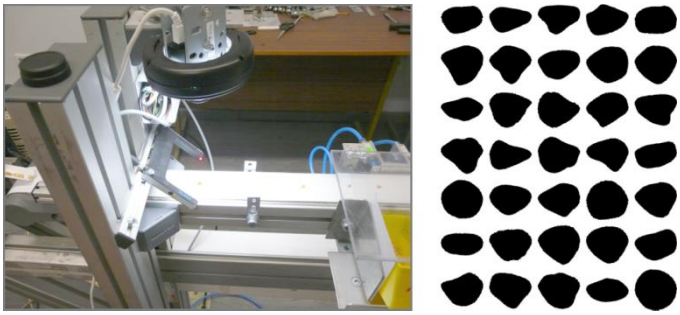
III. EXPERIMENTAL INVESTIGATIONS

A. *Experimental Setup, Data, and Normalization*

The main components of the system are presented in Fig. 3. Amber samples are dropped on the white conveyer bell from vibro feeder, the laser fork detects amber samples passing it, and then image is acquired by digital camera [23].

The setup was designed to minimize software related image normalization: the parameters like brightness, exposure, shutter time for each acquired image are fixed; the fast shuttering of camera helps in capturing "freezing" image of ambers moving on the conveyer; proper illumination is ensured by ring LED light lamps which is a scattered light source. The formed database consists of 6068 unique amber gemstone samples (Fig. 3. b).

Size of normalized image, the number of landmark points, and starting points requires additional investigations for each database individually. But for amber shapes database we used 256 pixels size of image, 64 landmark points - N , and 64 starting points - S .



a) b)

Figure 3. (a) the experimental setup; (b) 28 normalized samples from database.

B. *Shapes Matching by Similarity*

Many histogram-based shape matching methods, which compare composition of features, are not suitable for amber gemstones database. In this case a similarity measurement with ability to evaluate the sequence of spatial information like landmark points is needed. For this reason the CDF function was selected. It holds all distances from centroid to points of landmark in a sequential order. The two images matching may be done by shifting CDF and calculating the absolute difference between CDF of two shapes (Fig. 4). This approach is invariant to rotation and some results are shown in Fig. 4. Twelve most similar samples were retrieved from amber gemstones database for each of four query images.

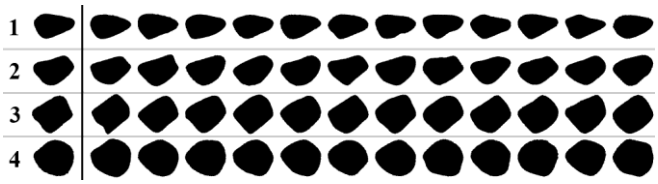
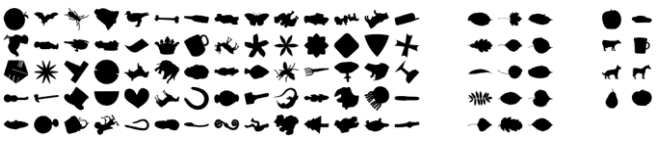


Figure 4. 12 nearest neighbors for four samples.

Although using 1-nearest-neighbor accuracy is high, CDF comparison has two main flows. Very similar CDF vectors still may represent different shapes. For example in MPEG7 CE-Shape-1 database some "sea snake" and "stef" shapes have similar CDF. Another problem with CDF arises using shift matching. There is no guarantee that the both CDF vectors will be shifted and oriented correctly. In such case of miss orientation the matching is inappropriate. And lastly pairwise matching is very time consuming process. That's why we have propose a DT model based technique.

Also, the proposed approach was tested on well know public databases like MPEG7 CE-Shape-1 [24], ETH-80 [25], and Swedish leafs [26] (Fig. 5).



a) b) c)

Figure 5. Typical shapes images, one image from each class: (a) MPEG7 CE-Shape-1; (b) Swedish leafs; (c) ETH-80.

Whereas images in those databases are labeled, the accuracy of classification was evaluated using 10-fold cross validation (Table I). Results are very promising comparing to results acquired by other researchers [1]-[2]-[4]-[5], because the proposed method is based on model which is better than pairwise matching methods in terms of speed performance for online sorting application.

TABLE I. OUR MODEL BASED APPROACH COMPARISON VERSUS KNN BASED APPROACHES BY ACCURACY PERFORMANCE. THE HIGHEST RESULT IS FROM TWO COMMON PAPERS WITH SHAPE DESCRIPTORS USING LOOCV.

Database	*Our approach (DT model)*	*Highest result (pairwise matching)*
MPEG7 CE-Shape-1	93.57 %	96.29 % [2]
Swedish leafs	93.81 %	95.33 % [1]
ETH-80	80.73 %	88.11 % [1]

C. Clustering by Shape Similarity

One third of amber gemstone images were selected for clustering and labeling. The other two thirds used to evaluate the classification.

The one third of amber gemstone images was selected and each pair was compared by absolute distance of CDF. This way the similarity matrix was created and used for clustering with *k*-medoids. It accepts similarity matrix as input and gives specified number of clusters. Also we have tried *k*-means clustering and the results are slightly better than using *k*-medoids clustering. The validity indices of generated clusters are presented in Fig. 6.

The generated clusters have good balance by amount of shapes in each cluster (Table. II). We tried to find optimal number of clusters, but it's not trivial. For example, we calculated Silhouette and Dunn's clustering validity indices (Fig. 6). The chart suggests picking as many clusters as possible or only few. But looking at individual images in clusters by "the eye of human being", it is obvious that optimal number of clusters is in range of 100-200, because individuals in clusters are very similar and still it is very easy for expert to label much smaller amount of clusters instead of all 2023 images one by one.

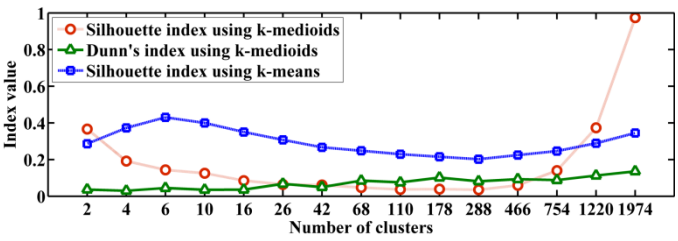
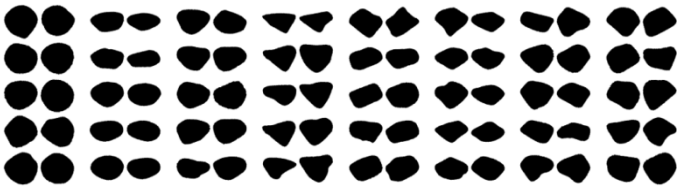


Figure 6. Clustering validity indices for amber gemstones database.

D. Classification by Similarity to Geometric Shapes

Training data were prepared by labeling each cluster to one of category from predefined set: circle, ellipse, oval (ellipse with only one symmetrical axis), triangle, rectangle, rhombus, trapezium, and trapezoid. Some of clusters were not trivial to label as they were similar to more than one geometric shape.

The testing is done on amber gemstone testing set images. Those images were not used for clustering. The results (Fig. 7) shows, that the proposed method is able to sort out amber by its similarity to selected geometric shapes using DT. Considering the high ambiguity between shapes, the method gives promising results.



a) b) c) d) e) f) g) h)

Figure 7. Randomly selected samples from classification results, 10 per category: (a) circles; (b) ellipses; (c) ovals; (d) triangles; (e) rectangles; (f) rhombus; (g) trapezium; (h) trapezoid.

The result classes are fairly balanced; all of them have members (Table II).

TABLE II. NUMBER OF AMBER GEMSTONES BY SHAPE CATEGORY.

Circles	*Ellipses*	*Ovals*	*Triangles*
236	829	1110	618
Rectangles	*Rhombus*	*Trapeziums*	*Trapezoids*
197	83	526	446

IV. CONCLUSIONS AND FUTURE WORK

In this paper, an approach for organic shapes classification by similarity to geometric shapes is proposed. The presented system is able to classify amber gemstone shapes to categories of geometric shapes defined by an expert even if organic shapes are very ambiguity for human perception.

Results have shown that by using CDF for query shape it is possible to find most similar shapes to the query shape. Although there is no guarantee that CDF vectors for matching will be shifted and oriented correctly. Also, very similar CDF vectors may represent different shapes, but this issue is more related to shapes with huge spatial variations like the ones exist in MPEG7 CE-Shape-1 database.

The proposed technique consists of two steps. In first step training data clustered and each cluster is labeled by an expert to one of category: circle, ellipse, oval (ellipse with only one symmetrical axis), triangle, rectangle, rhombus, trapezium, and trapezoid. In second step DT model is constructed using labeled training data. The DT model performance shows promising results.

The proposed technique was tested with three public databases. Since all databases are labeled the DT model can be created without clustering by dividing data to training and testing sets. DT model classification results using public databases with 10-fold cross validation are very close to

perhaps best known results (Table I) validated by leave one cross validation: for MPEG7 CE-Shape-1 - 93.57 % comparing to 96.29 %, for Swedish leafs - 93.81 % comparing to 95.33 %, and for ETH-80 – 80.73 % comparing to 88.11 %. But the proposed method is model based consumes much less time in preparing it and evaluating on testing data comparing to pairwise matching.

The main disadvantage of current database is that it is not labeled and there is no way to measure how well classification matches human perception of geometry forms. So, in future the database should be labeled and other shapes descriptors investigated.

V. REFERENCES

[1] H. Ling and D.W. Jacobs, "Shape Classification Using the Inner-Distance", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 29, No. 2, pp. 286-299, Feb. 2007.

[2] G. McNeill and S. Vijayakumar, "2D Shape Classification and Retrieval", IJCAI'05 Proceedings of the 19th international joint conference on Artificial intelligence, pp. 1483-1488, Jul. 2005.

[3] D. Zhang and G. Lu, "Shape-based image retrieval using generic Fourier descriptor", Signal Process. Image Commun., Vol. 17, No. 10, pp. 825-848, 2002.

[4] A. D. Lillo, G. Motta, and J. A. Storer, "Shape Recognition Using Vector Quantization", DCC '10 Proceedings of the 2010 Data Compression Conference, pp. 484-493, Mar. 2010.

[5] H. Rongxiang, J. Wei, L. Haibin, and H. Deshuang. "Multiscale Distance Matrix for Fast Plant Leaf Recognition", IEEE Transactions on Image Processing, Vol. 21, No. 11, pp. 4667-4672, Nov. 2012.

[6] F. Xiang, H. Yong, S. Dandan, and Z. Jiexian, "An Image Retrieval Method based on Hu Invariant Moment and Improved Annular Histogram", Elektronika ir elektrotechnika = Electronics and Electrical Engineering, ISSN 1392-1215, Vol. 19, No. 10, 2013.

[7] K. Okarma and P. Mazurek, "Application of Shape Analysis Techniques for the Classification of Vehicles", Transport Systems Telematics Communications in Computer and Information Science, Vol. 104, pp 218-225, 2011.

[8] Y. Mingqiang, K. Kidiyo, and R. Joseph, "A Survey of Shape Feature Extraction Techniques", Pattern Recognition, pp. 43-90, Nov. 2008.

[9] D. E. R. Clark, J. R. Corney, F. Mill, H. J. Rea, A. Sherlock, et al., "Benchmarking shape signatures against human perceptions of geometric similarity", Computer-Aided Design, Vol. 38, No. 9, pp. 1038–1051, Sep. 2006.

[10] B. Huang, J. Wu, D. Zhang, and N. Li, "Tongue shape classification by geometric features", Information Sciences, Vol. 180, No. 2, pp. 312–324, Jan. 2010.

[11] Q. Wang and K. L. Boyer, "The active geometric shape model: A new robust deformable shape model and its applications", Computer Vision and Image Understanding, Vol. 116, No. 12, pp. 1178–1194, Dec. 2012.

[12] S. S. Spasojevic, M. Z. Susic, and Z. M. Durovic, "Recognition and classification of geometric shapes using neural networks", 11th Symposium on Neural Network Applications in Electrical Engineering, pp. 71-76, Sep. 2012.

[13] I. Z. Mihu, A. Gellert, and H. V. Caprita, "Improved Methods of Geometric Shape Recognition Using Fuzzy and Neural Techniques", in Proc. of the 6th International Conference on Technical Informatics, Vol. 4, pp. 99-104, May 2004.

[14] E. Yildizer, A. M. Balci, T. N. Jarada, and R. Alhajj, "Integrating wavelets with clustering and indexing for effective content-based image retrieval", Knowledge-Based Systems, Vol. 31, pp, 55-66, July 2012.

[15] N. M. Portela, G. D. C. Cavalcanti, and T. I. Ren, "Semi-supervised clustering for MR brain image segmentation", Expert Systems with Applications, Vol. 41, No. 4, Part 1, pp. 1492-1497, Mar. 2014.

[16] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms", IEEE Trans. on Systems, Man, and Cybernetics, Vol. 9, No. 1, pp. 62-66, 1979.

[17] R. C. Gonzalez, R. E. Woods, and S. L. Eddins, Digital Image Processing Using MATLAB, New Jersey, Pearson Prentice Hall, 2004.

[18] S. Arlot and A. Celisse, "A survey of cross-validation procedures for model selection", Statistics Surveys, Vol. 4, No. 0, pp. 40-79, 2010.

[19] J. C. Dunn, "Well Separated Clusters and Optimal Fuzzy Partitions," Journal of Cybernetics, Vol. 4, No. 1, pp. 95-104, 1974.

[20] P. J. Rousseew, "Silhouettes: A graphical aid to the interpretation and validation of cluster analysis," Journal of Computational and Applied Mathematics, vol. 20, pp. 53-65, 1987.

[21] J. Han, M. Kamber, and A. K. H. Tung, "Spatial Clustering Methods in Data Mining: A Survey", in Geographic Data Mining and Knowledge Discovery, pp. 1–29, 2001.

[22] L. Breiman, J. Friedman, R. Olshen, and C. Stone. "Classification and Regression Trees", Boca Raton, FL: CRC Press, 1984.

[23] V. Raudonis, A. Lipnickas, A. Paulauskaitė-Tarasevičienė, L. Paulauskas, A. Balčius, and S. Paulauskas. "Expert knowledge based approach for automatic sorting and packing", in Journal of Vibroengineering / Vibromechanika, Lithuanian Academy of Sciences, Kaunas University of Technology, Vilnius Gediminas Technical University. Kaunas : Vibroengineering. ISSN 1392-8716. Vol. 15, no. 1, pp. 496-507, 2013.

[24] L. J. Latecki, R. Lakamper, and U. Eckhardt, "Shape Descriptors for Non-Rigid Shapes with a Single Closed Contour", in Proc. IEEE Conf. Computer Vision and Pattern Recognition, Vol. 1, pp. 424-429, 2000.

[25] B. Leibe and B. Schiele, "Analyzing Appearance and Contour Based Methods for Object Categorization," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, Vol. 2, pp. 409-415, 2003.

[26] O. J. O. Söderkvist, "Computer Vision Classification of Leaves from Swedish Trees", M.S. thesis, Linköping University, Sweden, 2001.