A cognitive evaluation procedure for contour based shape descriptors

Anarta Ghosh* and Nicolai Petkov

*Institute of Mathematics and Computing Science, University of Groningen,
P.O. Box. 800, 9700 AV Groningen, The Netherlands*

Abstract. Present image processing algorithms are unable to extract a neat and closed contour of an object of interest from a natural image. Advanced contour detection algorithms extract the contour of an object of interest from a natural scene with a side effect of depletion of the contour. Hence in order to perform well in a real world scenario, object recognition algorithms should be robust to contour incompleteness. With inspiration from psychophysical studies of the human cognitive abilities we propose a novel method to evaluate the performance of object recognition algorithms in terms of their robustness to incomplete contour representations. Complete contour representations of objects are used as a reference (training) set. Incomplete contour representations of the same objects are used as a test set. The performance of an algorithm is evaluated using the recognition rate as a function of the percentage of contour retained. The test framework is illustrated by using two contour based shape recognition algorithms which use a shape context and a distance multiset as shape descriptors. Three types of contour incompleteness, viz. segment-wise contour deletion, occlusion and random pixel depletion, are considered. In our experiments we use images from the COIL and MPEG-7 datasets. Both algorithms qualitatively perform similar to the human visual system in the sense that recognition performance monotonously increases with the degree of completeness and that they perform best in the case of random depletion and worst in the case of occluded contours. The distance multiset shape descriptor outperforms the shape context in this test especially for high levels of incompleteness.

Keywords: COIL, deletion, depletion, distance multiset, Gollin, incompleteness, MPEG-7, occlusion, psychophysics, shape context

1. Introduction

In Fig. 1 we illustrate the limitations of the image processing algorithms in the context of extracting a neat and closed contour of an object of interest from a natural scene. In the left image we see a gazelle in its natural surroundings. The middle image is obtained from the left image using a bank of Gabor energy filters [1]. In this image, extraction of the contour of the object of interest, viz. gazelle, was intended. However along with the contour of the gazelle it also contains a large number of texture edges which make it impossible to use any contour based object recognition algorithm to detect the gazelle in the natural scene. In the right-most image we see that an advanced contour detection algorithm based on surround suppression [1,2] gets rid of those texture edges but at the same time it has a negative side effect of depleting the contour of the object of interest. Hence in order to perform well in a real world scenario it is imperative that contour based object recognition algorithms are robust to incomplete contour representations.

---

*Corresponding author. E-mail: anarta@cs.rug.nl.
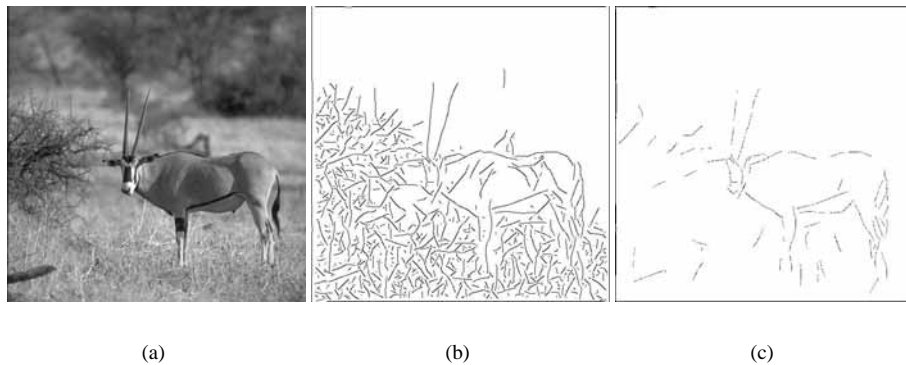
| (a) | (b) | (c) |

Fig. 1. (a) Image of a gazelle in its natural habitat. (b) Result of edge detection with a bank of Gabor energy filters. (c) Result of contour detection by a bank of Gabor energy filters augmented with a biologically motivated surround suppression of texture edges [1]. The contours of the object of interest are better visible in the latter image but the suppression of texture edges has resulted in a partial contour depletion. (Both algorithms are available as web applets at www.cs.rug.nl/~petkov)

Moreover, if the object recognition algorithms are required to perform similar to the human visual system, robustness to incomplete representations is very important. For example we can easily recognize the elephant and the umbrella from their incomplete contour representations depicted in Fig. 2 (e.g. set III and IV). This aspect of the human ability to recognize objects from their incomplete contour representations is extensively studied in the field of psychophysics [3–6]. In [3] psychologist E. S. Gollin investigated this aspect of the human perception in details. He conducted four experiments with different groups of children with varying developmental characteristics (intelligence quotient, mental and chronological age) and a group of adults. Through his experiments he tried to find answers to the following two questions: (1) How does training affect the recognition performance in case of incomplete representations? (2) In order to be recognized, how complete the contours of common objects need to be? He used sets of contour images with different degrees of incompleteness (Fig. 2). Through his experiments he found that the ability of humans to recognize objects depends on developmental characteristics and is improved by a proper training procedure.

Inspired by the psychophysical studies presented in [3–6] and due to its practical importance explained above we put forward a novel characteristics, viz. *robustness to incomplete contour representations*, that any contour based object recognition system/algorithm should have. We choose an ideal situation where: (i) the complete contour representations of objects are taken as the reference set (memory) of a recognition system, (ii) incomplete contour representations of the same objects are derived from the afore mentioned complete representations and are used as a test set to evaluate the performance of contour based object recognition algorithms. Along with Gollin's method [3] of segment-wise contour deletion (like set I to set IV of Fig. 2), we also consider other types of incompleteness, viz. occlusion and random pixel depletion. The corresponding studies are named **segment-wise deletion test, occlusion test and depletion test**.

The shape recognition methods that can be studied in the proposed framework must use contour information. Unless necessary modifications are done, methods which use other type of information fall outside the scope of this study. For instance, Gavrila [7] proposes a method based on the distance transform in which every point of a binary object is characterized by its distance to the object's border. In our study objects are represented by their contour points only and hence, the distance transform is not informative. Due to the same reason Goshtaby's shape matrix [8] cannot be directly assessed in this framework either. For further discussion on shape analysis and object recognition methods see e.g. [9–16].
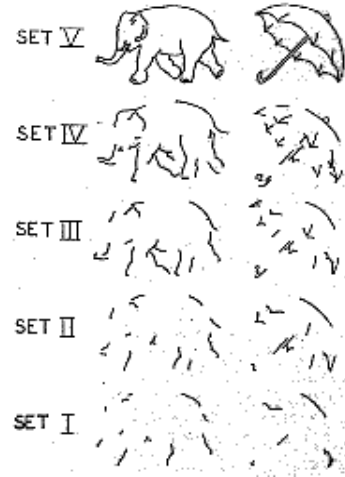
Fig. 2. Example of image sets used in Gollin's original test [3]. The images in set V are complete contour representations and the other sets are derived from set V by removing segment-wise an increasing fraction of the contour. (Reproduced with permission of author and publisher from: Gollin E. S. Developmental studies of visual recognition of incomplete objects. *Perceptual and Motor Skills*, 1960, 11, 289–298. ©Southern University Press 1960.).

We study simplified versions of the *shape context* based algorithm described in [17] and the *distance multiset* based algorithm described in [10] with respect to their robustness to contour incompleteness of different types. In Section 2 we briefly describe these algorithms. In Section 3 we present the experimental design and the methodology. The achieved results, a detailed discussion on the performances of the aforementioned algorithms in the proposed test procedure and some further insights into the evaluation framework are presented in Section 4. A summary and conclusions are presented in Section 5.

2. Shape recognition algorithms

The recognition of objects, in the algorithms studied below, is done by computing dissimilarity between the contour representations of two objects by using a point correspondence paradigm. Shape descriptors associated with the points are used to find the point correspondences. To maintain brevity and focus on the illustration of the test framework we use simplified versions of the algorithms described in [10,17].

For a point p in the contour of an object $\mathcal{O}$, having N points, the **distance multiset** is formally defined as follows [10]:

$$D_N^{\mathcal{O}}(p) = (ln(d_1(p)), ln(d_2(p)), \ldots, ln(d_{N-1}(p)))$$ (1)

where $d_j(p), j = 1 \ldots N - 1$ is the Euclidean distance between p and its jth nearest neighbor in $\mathcal{O}$. In this approach the shape of an object $\mathcal{O} \equiv \{p_1 \ldots p_N\}$ defined by a set of N points, is described by the set of distance multisets in the following way:

$$S_{\mathcal{O}}^{DM} \equiv \{D_N^{\mathcal{O}}(p) | p \in \mathcal{O}\}.$$ (2)

Next, a cost of matching two distance multisets is defined as follows. Consider the multisets

$$X = (x_1, x_2, \ldots, x_M),$$ (3)

$$Y = (y_1, y_2, \ldots, y_N) \tag{4}$$

where $M \leqslant N$. Let A be the following $M \times N$ matrix of absolute values of pair-wise differences of elements of X and Y:

$$A_{i,j} = |x_i - y_j|, \; i = 1 \ldots M, j = 1 \ldots N. \tag{5}$$

Let π be a one-to-one mapping from the set $\{1, \ldots, M\}$ to the set $\{1, \ldots, N\}$ and let Π be the set of all such mappings. The mapping π defines an assignment of an unique element $y_{\pi(i)} \in Y$ to each element $x_i \in X$. The cost $c_\pi(X, Y)$ of a mapping/assignment $\pi \in \Pi$ is defined as follows:

$$c_\pi(X, Y) = \sum_{i=1}^{M} A_{i, \pi(i)} \tag{6}$$

Let c be the minimum of the costs of all such possible mappings:

$$c(X, Y) = \min\{c_\pi(X, Y) | \pi \in \Pi\} \tag{7}$$

We now define the cost $c_{i,j}^{DM}$ of matching a point p_i in an object $\mathcal{O}_1$ represented by M contour points to a point q_j in an object $\mathcal{O}_2$ represented by N contour points, $M \leqslant N$, using the definition of c in the following way:

$$c_{i,j}^{DM} \equiv c(D_N^{\mathcal{O}_1}(p_i), D_M^{\mathcal{O}_2}(q_j)) \tag{8}$$

Note that $D_N^{\mathcal{O}_1}(p_i)$ and $D_M^{\mathcal{O}_2}(q_j)$ are sorted in ascending order by the definition of a distance multiset. To compute $c(D_N^{\mathcal{O}_1}(p_i), D_M^{\mathcal{O}_2}(q_j))$ efficiently, we use the algorithm described in [18].

The **shape context** [17], of a point p, belonging to the contour of an object is a two-dimensional histogram in a log-polar coordinate system that gives the distribution of contour points in the surroundings of p. Let an object $\mathcal{O}$ be represented by a set of contour points, $\mathcal{O} \equiv \{p_1 \ldots p_N\}$. Formally, the authors of this method define the shape context of a point $p \in \mathcal{O}$ as a vector in the following way:

$$H_K^{\mathcal{O}}(p) = (h_1(p), h_2(p), \ldots, h_K(p)) \tag{9}$$

where

$$h_k(p) = card\{q \neq p | q \in \mathcal{O}, (q - p) \in bin(k)\}, \tag{10}$$

and K is the total number of histogram bins. The bins are constructed by dividing the image plane into K partitions (in a log-polar coordinate system) with p as the origin. In this study we use 5 intervals for the log distance, and 12 intervals for the polar angle, so $K = 60$. To improve performance, in this study we normalize $H_K^{\mathcal{O}}(p)$ by the total number of contour pixels of the concerned object. The shape of the object is described using the set of shape contexts associated with all contour points in the following way:

$$S_{\mathcal{O}}^{SC} \equiv \{H_K^{\mathcal{O}}(p) | p \in \mathcal{O}\}. \tag{11}$$

The cost of matching a point p_i belonging to the contour of an object $\mathcal{O}_1$, having M points, to a point q_j belonging to the contour of an object $\mathcal{O}_2$, having N points is defined as follows:

$$c_{i,j}^{SC} \equiv \frac{1}{2} \sum_{k=1}^{K} \frac{[h_k(p_i) - h_k(q_j)]^2}{h_k(p_i) + h_k(q_j)} \tag{12}$$

Fig. 3. Row 1: Sample of the COIL-20 database images which are used as the image dataset. Row 2: Rescaled contour images that are considered as complete representations.

Next the dissimilarity between shapes is computed using the cost-matrices of point-wise matching defined in Eqs (8) and (12) as follows:

$$d^{DM/SC}(S_{\mathcal{O}_1}^{DM/SC}, S_{\mathcal{O}_2}^{DM/SC}) \equiv \sum_{i=1}^{M} \min\{c_{i,j}^{DM/SC} | j = 1 \ldots N\} \tag{13}$$

3. Experimental design and methodology

3.1. Image set

As an image dataset we choose images from the the Columbia University Image Library (COIL-20) database. It contains 1440 different images divided in 20 classes, each of 72 similar objects. We choose one object from each class (Fig. 3, row 1) and extract the contours of the object using Gabor filters [1]. The resulting 20 contour images are rescaled in such a way that the diameter (maximum Euclidean distance between two contour pixels) is approximately the same (76 pixels) for all objects, cf. row 2 of Fig. 3. These 20 rescaled contour images are used as reference images in our experiments. The set of these images corresponds to the complete representations, set V of Fig. 2, used in Gollin's original study and form the "memory" of the recognition system.

For the *segment-wise deletion test* incomplete representations (Fig. 4) are constructed by randomly removing continuous segments of the contours and retaining a given percentage of contour pixels from the above mentioned complete contour representations. For the *occlusion test* incomplete representations are created by removing a given percentage of consecutive contour pixels starting from the leftmost (Fig. 5, row 1) or the rightmost pixel (Fig. 5, row 2) of an object. For the *depletion test* the incomplete representations (Fig. 6) are obtained by randomly removing a given percentage of pixels from the contours of the complete contour representations.

In our experiments the percentages of retained pixels are chosen in the following way: 2% to 4% in steps of 1%, 5% to 85% in steps of 5%, and 100% for the depletion tests, 5% to 85% in steps of 5%, and 100% for the segment-wise deletion test and for the occlusion test. For each type (segment-wise deletion, occlusion and depletion) and degree of contour image degradation we create 20 test images. All complete contour images and incomplete contour images obtained with different types and percentages of incompleteness are available in the web-site www.cs.rug.nl/~petkov.
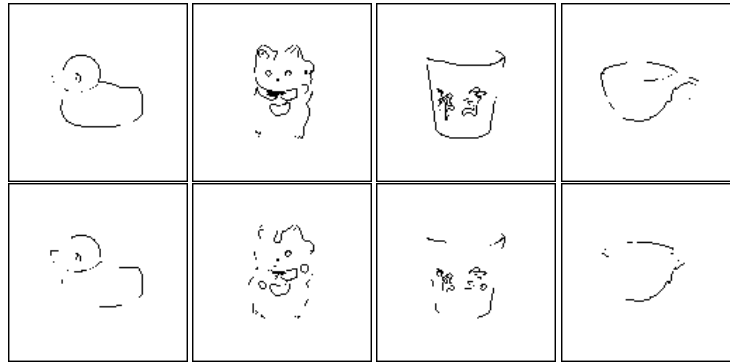
Fig. 4. Segment-wise deleted contour representations of objects (they correspond to the incomplete representations of Gollin's original study, sets I to IV of Fig. 2). The images are obtained by retaining 70% (row 1) and 50% (row 2) of the contour pixels (compare with row 2 of Fig. 3).

Fig. 5. Occluded contour representations of objects. The images are obtained by removing 30% of the contour from left (row 1) and right (row 2).
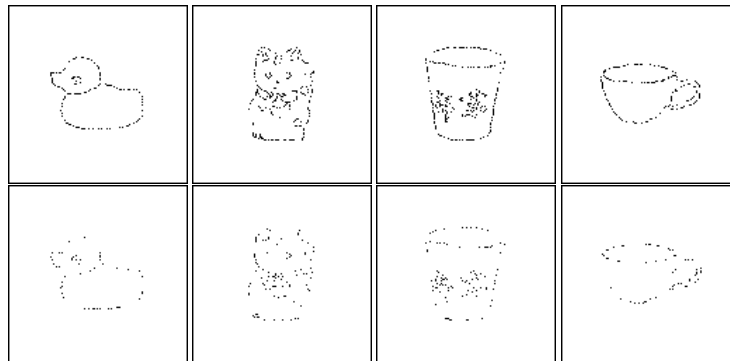

Fig. 6. Depleted contour representations of objects which are constructed by randomly removing 50% (row 1) and 80% (row 2) of the contour pixels.

3.2. Methodology

An incomplete representation (segment-wise deleted or depleted or occluded contour image) obtained from one of the 20 reference images is compared with all 20 reference images and a decision is taken about
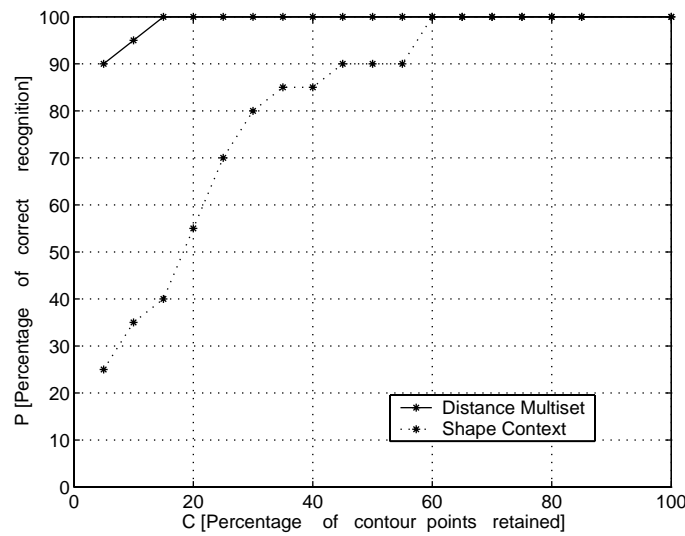
Fig. 7. Results of the segment-wise deletion test with a subset of the COIL-20 dataset. The distance multiset method gives 100% recognition rate when more than 15% of the contour is retained. The shape context method performs reasonably well ($\geqslant$ 90% recognition rate) when more than 40% of the contour points are retained.

which reference image the degraded image is most similar to (nearest neighbor search). The comparison is based on a shape dissimilarity computed using a given shape comparison algorithm described in Section 2. If the nearest neighbor is the reference image from which the degraded image was obtained, the recognition is considered correct, otherwise incorrect. If the nearest neighbor is found to be not unique then the recognition is also considered incorrect. For each of the three tests (segment-wise deletion, occlusion, depletion) and for each degree of contour image degradation, the corresponding 20 test images are compared with each of the 20 reference images and the percentage of correct recognition is determined. The percentage of correct recognition P is observed as a function $P(c)$ of the percentage c of retained contour pixels. In the case of occlusion test the percentage of correct recognition is calculated by averaging the correct recognition rates with left and right occluded images for a given percentage of retained contour.

4. Results and discussion

4.1. Performance of the algorithms

Figures 7, 8 and 9 show the results of our experiments. In all three tests and for both shape comparison algorithms, the recognition rate is a monotonously increasing function of the percentage of contour retention. In this respect the considered algorithms resemble the human visual system [4–6]. Both methods perform worst in the occlusion test and best in the depletion test, which also conforms with the recognition performance of humans, as occluded contour images carry the least amount of shape information and depleted contour images carry maximum shape information in the context of human visual perception.

In the case of the segment-wise deletion test (Fig. 7) and the occlusion test (Fig. 8), the performance of the distance multiset method is appreciably better than that of the shape context method for any
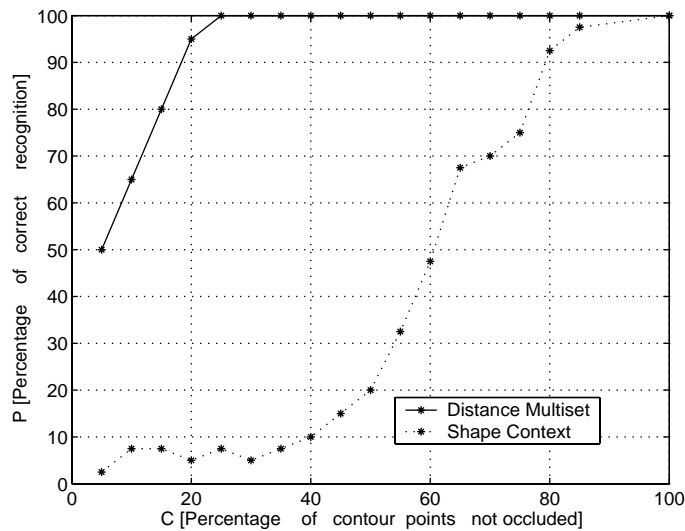
Fig. 8. Results of the occlusion test with a subset of the COIL-20 dataset. The shape context method is particularly affected by occlusion because the shape context descriptors of contour points near the occlusion boundary are radically different from the shape contexts of the same points in the complete contours.
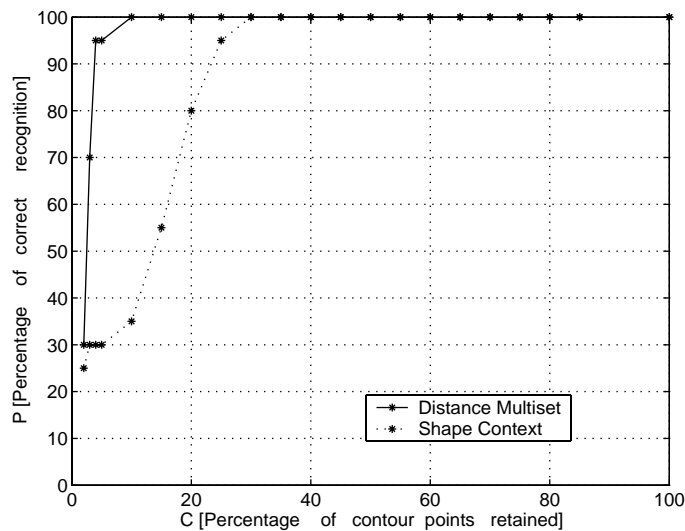

Fig. 9. Results of the depletion test. The distance multiset method and the shape context method perform very well for more than 5% and 25% retention of contour pixels, respectively.

percentage of retained contour pixels. From the results of the depletion test (Fig. 9) we see that both the shape context method and the distance multiset method perform very well in recognizing objects with depleted contour representations, if more than 25% and 5%, respectively, of the contour points are retained. The distance multiset method outperforms the shape context method when the degree of depletion is very high, i.e. a very low percentage (less than 25%) of the pixels are retained.

For both methods the results of the occlusion test are worse than the results in other tests. This is more evident for the shape context method and can be explained as follows: a contour point near the
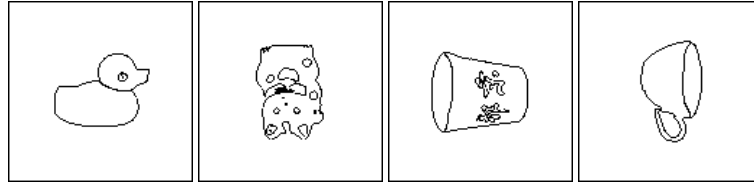
Fig. 10. Transformed reference images. The images are obtained by applying different isometric transformations to the images illustrated in the second row of Fig. 3.

occlusion boundary has radically different shape context from the same contour point in the reference (unoccluded) object contour, since all the contour points on one side of the occlusion boundary are missing. Hence, such a point will have a large contribution to the dissimilarity between occluded and unoccluded contours.

4.2. Discussion

In general, the better performance of the distance multiset method can be explained by the fact that the proposed tests give advantage to algorithms which yield zero dissimilarity in a comparison of two objects represented by two sets of points where one is a subset of the other. This property of the distances multiset is explained in more detail below. Let $\mathcal{A}, \mathcal{B}, \mathcal{C} \in \mathbf{R}^2$ and $\phi : \mathbf{R}^2 \rightarrow \mathbf{R}^2$ be such that for any $\mathbf{x} \in \mathbf{R}^2$, $\phi(\mathbf{x}) = \mathbf{Lx} + \mathbf{t}$, where $\mathbf{L}$ being a 2×2 orthogonal matrix ($|det(\mathbf{L})| = 1$) and $\mathbf{t} \in \mathbf{R}^2$. Note that ϕ is an isometry.

Proposition:
Case 1: $\mathcal{A} = \{\phi(\mathbf{x})|\mathbf{x} \in \mathcal{B}\}$ and $\mathcal{C} \subset \mathcal{B}$.
Case 2: $\mathcal{B} \subset \mathcal{A}$ and $\mathcal{C} = \{\phi(\mathbf{x})|\mathbf{x} \in \mathcal{B}\}$.
In both cases the following holds:

$$d^{DM}(S_\mathcal{C}^{DM}, S_\mathcal{A}^{DM}) = 0 \tag{14}$$

where $S_\mathcal{C}^{DM}$ and $S_\mathcal{A}^{DM}$ are the shapes, described by distance multisets, corresponding to C and A, respectively.

The proof of this proposition follows trivially from the proof of the lemma presented in [9].

Case 1 of the proposition corresponds to the fact that if $\mathcal{B}$ represents an original reference object (see second row of Fig. 3) then $\mathcal{A}$ represents a transformed versions of it (Fig. 10) and $\mathcal{C}$ represents an incomplete representation (Figs 4, 5 and 6). We performed segment-wise deletion, occlusion and random pixel depletion tests on the distance multiset method taking objects such as those illustrated in Fig. 10 as the reference set and objects such as those illustrated in Figs 4, 5 and 6 as the incomplete representations. The results are shown in Figs 14, 15 and 16. Comparing the results in Figs 14, 15 and 16 with the results presented in Figs 7, 8 and 9, respectively, we find no difference in the performance of the distance multiset method as expected from the proposition.

Case 2 of the proposition corresponds to the fact that if $\mathcal{A}$ represents an original reference object (see second row of Fig. 3) then $\mathcal{B}$ represents an incomplete contour image (Figs 4, 5 and 6) and $\mathcal{C}$ represents the transformed version of the incomplete contour image represented by $\mathcal{B}$ (Figs 11, 12, 13). Similar to Case 1 in our experiments with images such as those shown in the second row of the Fig. 3 as the reference set and incomplete contour images such as those depicted in Figs 11, 12 and 13 as the test set, we found no change in the performance of the distance multiset method. This is a logical result because

Fig. 11. Transformed segment-wise deleted test images. Different isometric transformations are applied to the images depicted in the first row of Figure 4 to obtain these images.
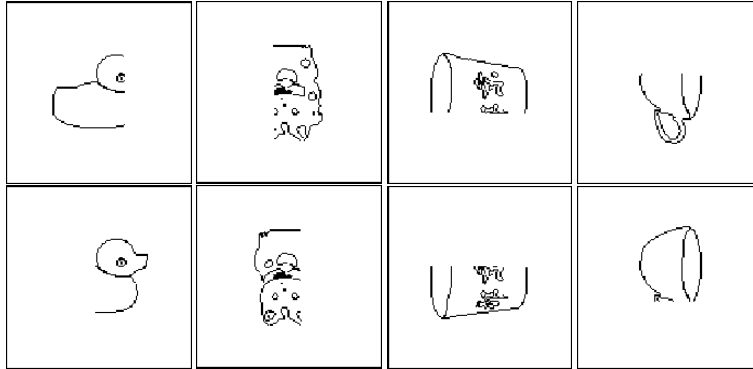

Fig. 12. Transformed occluded objects. The images are derived through different isometric transformations of the images shown in Fig. 5.
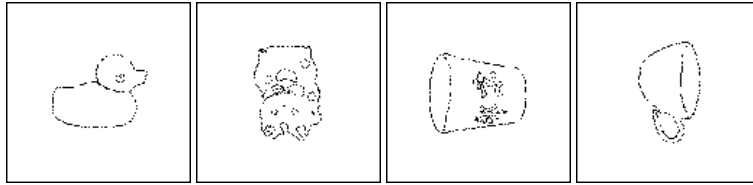

Fig. 13. Transformed randomly depleted contour images. Different isometric transformations are performed on the images illustrated in the first row of Fig. 6 to get these images.

the two cases differ only in the order in which the transformation ϕ and depletion/occlusion/deletion are applied. The two types of operation are commutative.

The proposition also reveals the fact that the recognition by the distance multiset method will be incorrect only when the nearest neighbor of the test object in the reference set is not unique. We can also infer that the performance of the distance multiset method will be invariant under isometric transformations of the incomplete contour representations which emphasizes the use of distance multiset method in our study instead of just matching pixels to calculate the dissimilarity between the shapes of objects.

In our experiments described in Section 3, i.e. in the proposed evaluation procedure, we consider ϕ as an identity transformation ($\mathbf{L}$ is a 2×2 identity matrix and $\mathbf{t} = \mathbf{0}$).

The above proposition does not hold for the shape context method, but this method can be modified in such a way that the relation (14) can be approximately fulfilled. Specifically, we normalize the shape context $H_K^{\mathcal{O}}(p)$ by dividing its elements by the total number of points $card(\mathcal{O})$ in the corresponding object $\mathcal{O}$. If $\mathcal{O}' \subset \mathcal{O}$ is an incomplete representation derived from $\mathcal{O}$ and $H_K^{\mathcal{O}'}(p)$ is the normalized
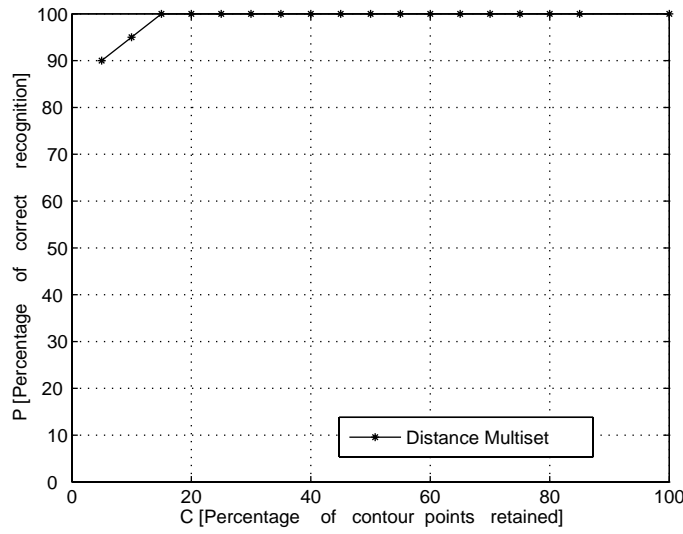
Fig. 14. Results of the segment-wise deletion test of the distance multiset method in the scenario described in Case 1 of the proposition.
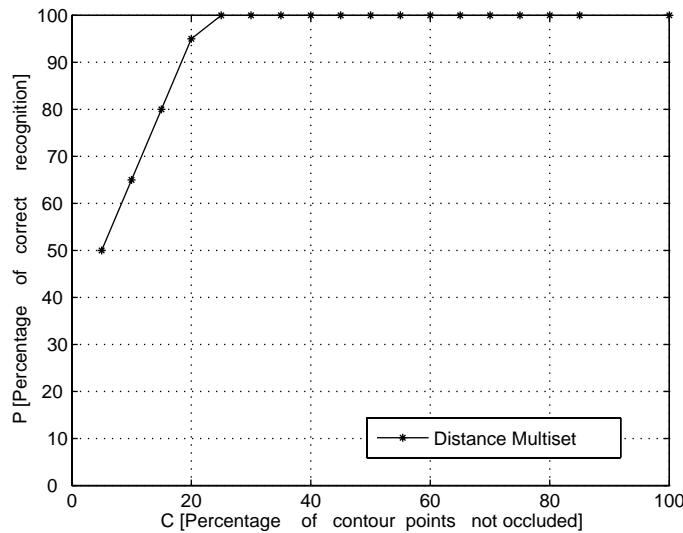

Fig. 15. Performance of the distance multiset method in the occlusion test in the scenario described in Case 1 of the proposition.

(by $card(\mathcal{O}^{'})$) shape context of a point p ($p \in \mathcal{O}^{'}$) in this incomplete representation, the relation $H_K^{\mathcal{O}^{'}}(p) \approx H_K^{\mathcal{O}}(p)$ will hold for modest degrees of contour deletion because the ratio of the number of contour points in each bin to the total number of points will be approximately the same for the complete and the incomplete contour representations. Hence, $d^{SC}(S_{\mathcal{O}}^{SC}, S_{\mathcal{O}'}^{SC}) \approx 0$ for the normalized shape contexts.

We performed experiments with and without the above mentioned normalization of the shape context, Figs 17, 18 and 19. There is a significant performance improvement in the segment-wise deletion and the depletion tests due to the normalization procedure. This justifies the use of this procedure in the
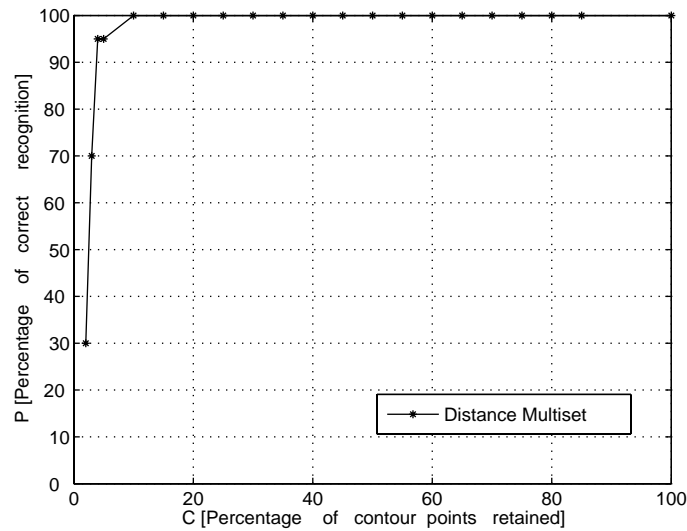
Fig. 16. The depletion test results of the distance multiset method in the situation described in Case 1 of the proposition.
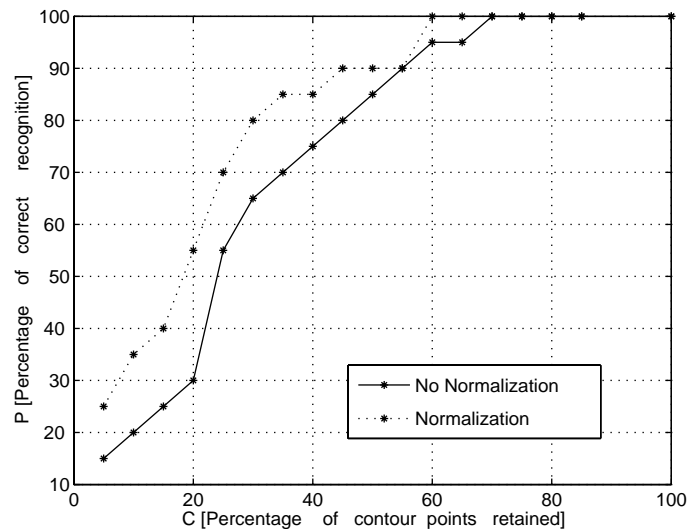

Fig. 17. Results of the segment-wise deletion test applied to the shape context method with and without the normalization procedure described in the text of the paper. The improvement in the performance of the shape context method due the normalization procedure is significant in the segment-wise deletion test.

experiments whose results are shown in Figs 7, 8 and 9.

4.3. Further insights

As the scope of this paper is to introduce a new test framework, it is important to check if the conclusions drawn from it are consistent across datasets. We carried out experiments using a second set of images obtained from the MPEG7 silhouette [19] database. It contains 1400 images divided in 70 classes, each of 20 similar objects (e.g. apple, bird, bat, etc.). We choose one object from each class and extract the
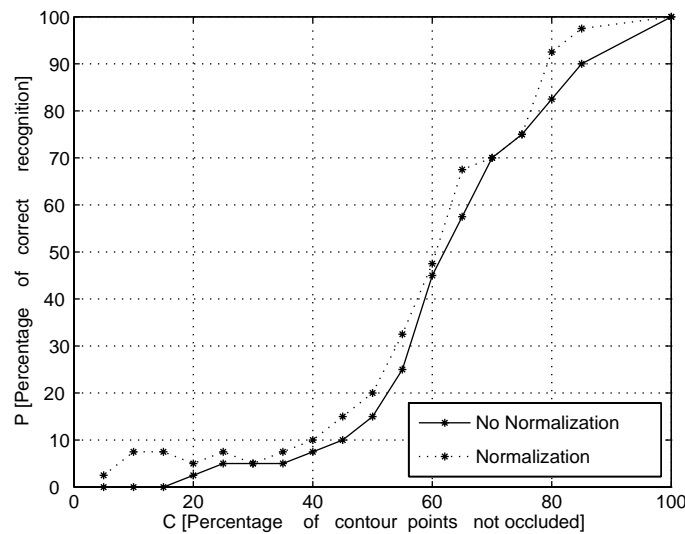
Fig. 18. Performance of the shape context method in the occlusion test with and without the normalization procedure. In the occlusion test the performance of the shape context method is slightly improved due to the normalization procedure.
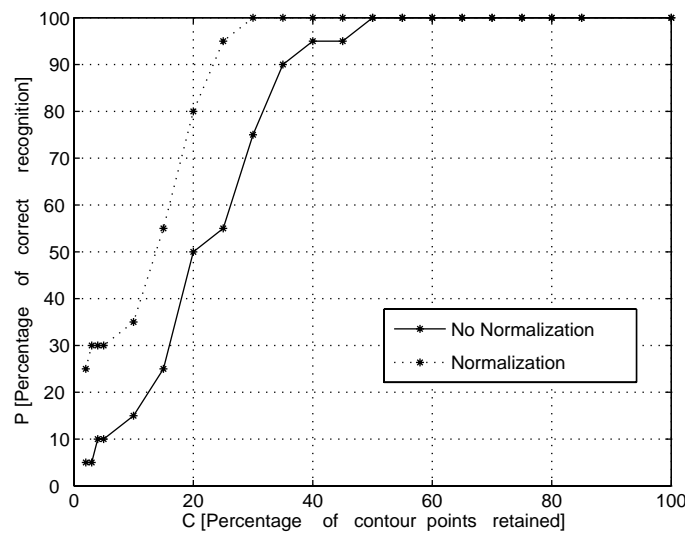

Fig. 19. Results of the depletion test in the case of the shape context method with and without the normalization. A significant performance improvement of the shape context method is observed in the depletion test due to the normalization procedure.

contours of the object using Gabor filters [1]. The resulting 70 contour images are rescaled in such a way that the diameter (maximum Euclidean distance between two contour pixels) is approximately the same (76 pixels) for all objects. We followed the same procedure used in the the case of the COIL-20 dataset to construct the incomplete contour images and performed the proposed tests. Compared to the results with COIL-20 dataset (Figs 7, 8 and 9) no qualitative difference in the performances of the algorithms was found. For a detailed discussion on these results see [9].

The *object size* can have effect on the results of the proposed test through (a) the resolution of the reference objects and (b) a possible mismatch between the size of a reference object and a test object.

Regarding the resolution of the reference objects, in our experiments we found that for a given percentage of contour degradation (by any method) the performance of the algorithms grows with the diameter of the reference objects. To eliminate this effect and to standardize the test procedure we rescaled the reference contour images to a fixed diameter (76 pixel units). The problem of a possible mismatch between the sizes of reference and test objects can be dealt with either by using scale invariance procedures prescribed in [10,17] or by using a multiscale approach. The scale issue is discussed in more detail in [9].

A good performance in the proposed tests does not guarantee a good performance in other respects, e.g. robustness to shape or size variation. Hence, a good performance in the proposed tests should be considered as a *necessary condition* for object recognition methods to perform well in a real world scenario but not as a sufficient one. We are not aware of any evaluation procedure for shape recognition methods which is sufficient in such respect. The basic framework of the tests proposed in this paper can easily be extended to test robustness of algorithms to more than one criterion, e.g. shape variations along with contour incompleteness [9].

5. Summary and conclusion

We propose a novel method for evaluation of contour based shape recognition algorithms in terms of their robustness to incomplete contour representations. To summarize the test framework, we put forward the following procedure:

(Step 1) Take a set of images of objects and extract contours. Rescale the contour images in such a way that the diameters of the objects are approximately the same, say 76 pixel units. (Step 2) Train the recognition system with these complete contour representations. (Step 3) Construct different sets of incomplete representations from the complete contour representations, quantifying the level of incompleteness using the percentage of contour pixels retained. (Step 4) Evaluate the recognition performance of the system by computing the recognition rate as a function of the percentage of contour pixels retained in the incomplete representations. We created a test database and made it publicly available at www.cs.rug.nl/~petkov/.

Shape descriptors based object recognition algorithms have been evaluated and compared using various characteristics like invariance, uniqueness and stability [20]. Marr and Nishihara [21] proposed three criteria for judging the effectiveness of a shape descriptor, viz. accessibility, scope and uniqueness, stability and sensitivity. Brady [22] put forward a set of criteria for representation of shape, viz. rich local support, smooth extension and propagation. A detailed survey and comparison of shape analysis techniques on the basis of some of the above mentioned criteria can be found in [11]. In the current work, motivated by characteristics of the human visual system [3], we propose an additional new criterion, viz. robustness to contour incompleteness to compare and characterize contour based shape recognition algorithms using their performance in recognizing objects with incomplete contours. We are not aware of any such comparison and characterization in the present literature.

We illustrated the test framework with two shape recognition methods based on the shape context and the distance multiset. Other shape recognition methods such as those based on Hausdorff measure [23, 24], wavelet descriptors [25], dynamic programming [26], graph matching [27], curve alignment [28], can also be studied in this framework. As the main objective of the research presented in this article is to introduce a test framework, motivated by the properties of human visual perception, an exhaustive comparison of different methods under this framework is beyond the scope of this paper.

In our illustrative experiments we found that: (1) The distance multiset shape descriptor outperforms the shape context in this framework, especially for high level of incompleteness. (2) Both methods mimic

the human visual system in the sense that their performances are best in the depletion test and worst in the occlusion test and the recognition rates monotonically improve with the degree of completeness of object contours.

The main conclusions of the research presented in this paper are as follows: (a) The robustness of contour based shape recognition algorithms to incompleteness of contour representations is an important aspect of any contour based objects recognition system. (b) The tests defined and proposed in this paper provide an adequate framework for assessing the above mentioned robustness and can be used as standard test procedures for any contour based object recognition algorithm.

References

[1] C. Grigorescu, N. Petkov and M. Westenberg, Contour detection based on nonclassical receptive field inhibition, *IEEE Transactions on Image Processing* **12** (July 2003), 729–739.

[2] C. Grigorescu, N. Petkov and M.A. Westenberg, Contour and boundary detection improved by surround suppression of texture edges, *Image and Vision Computing* **22** (2004), 609–622.

[3] E.S. Gollin, Developmental studies of visual recognition of incomplete objects, *Perceptual and Motor Skills* **11** (1960), 289–298.

[4] N.P. Foreman and R. Hemmings, The Gollin incomplete figures test: A flexible, computerised version, *Perception* **16** (1987), 543–548.

[5] V. Chihman, V. Bondarko, Y. Shelpin and M. Danilova, Fragmental figure perception, *Perception* **33**(Supplement), 2004, 76a.

[6] Y. Shelepin, O. Vahromeeva, A. Harauzov, S. Pronin, N. Foreman and V. Chihman, Recognition of incomplete contour and half-tone figures, *Perception* **33**(Supplement) (2004), 85c.

[7] D.M. Gavrila, Multi-feature hierarchical template matching using distance transforms, in *International Conference on Pattern Recognition* (*ICPR '98*), Brisbane, Australia, 1998, 439–444.

[8] A. Goshtaby, Description and discrimination of planar shapes using shape matrix, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **7** (Nov. 1985), 738–743.

[9] A. Ghosh and N. Petkov, Robustness of shape descriptors to incomplete contour representations, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **27**(11) (November 2005), 1793–1804.

[10] C. Grigorescu and N. Petkov, Distance sets for shape filters and shape recognition, *IEEE Transactions on Image Processing* **12**(10) (Oct. 2003), 1274–1286.

[11] S. Loncaric, A survey of shape analysis techniques, *Pattern Recognition* **31**(8) (1998), 983–1001.

[12] R.C. Veltkamp and M. Hagedoorn, *State of the art in shape matching,* Technical Report UU-CS-1999-27, Utrecht University, 1999.

[13] G. Nagy, Twenty years of document image analysis in PAMI, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **22** (Jan. 2000), 38–62.

[14] T. Pavlidis, Algorithms for shape analysis of contours and waveforms, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **2** (1980), 301–312.

[15] Y. Aloimonos, Visual shape computing, *Proceedings of IEEE* **76** (1988), 899–916.

[16] R. Basri, L. Costa, D. Geiger and D. Jacobs, Determining the similarity of deformable shapes, *Vision Research* **38** (1998), 2365–2385.

[17] S. Belongie, J. Malik and J. Puzicha, Shape matching and object recognition using shape contexts, *IEEE Transaction on Pattern Analysis and Machine Intelligence* **24**(24) (2002), 509–522.

[18] N. Petkov, *Algorithm for the cost of an optimal assignment of two sets of real numbers,* Technical report, 2003-9-07, Institute of Mathematics and Computing Science, University of Groningen, 2003.

[19] L.J. Latecki, R. Lakämper and U. Eckhardt, Shape descriptors for non-rigid shapes with single closed contour, *In Proc. of IEEE Conf. on Computer Vision and Pattern Recognition*, 1998, 424–429.

[20] F. Mokhtarian and A.K. Mackworth, A theory of multiscale, curvature-based shape representation for planar curves, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **14**(8) (1992), 789–805.

[21] D. Marr and H.K. Nishihara, Representation and recognition of the spatial organization of three dimensional shapes, *In Proc. Roy. Soc. London* **B200** (1978), 269–294.

[22] M. Brady, Criteria for representations of shape, in: *Human and Machine Vision,* J. Beck, B. Hope and A. Rosenfeld, eds, Academic Press, 1983, 39–84.

[23] D. Huttenlocher, G. Klanderman and W. Rucklidge, Comparing images using Hausdorff distance, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **15** (Sep. 1993), 850–863.

[24] D. Huttenlocher, H. Lilian and C. Olson, View-based recognition using an eigenspace approximation of Hausdorff measure, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **21** (Sep. 1999), 951–955.

[25] G.C.-H. Chuang and J. Kuo, Wavelet descriptor of planar curves: theory and application, *IEEE Transactions on Image Processing* **5** (Jan. 1996), 56–70.

[26] E.G.M. Petrakis, A. Diplaros and E. Milios, Matching and retrieval of distorted and occluded shapes using dynamic programming, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **24** (Nov. 2002), 1501–1516.

[27] A.D.J. Cross and E.R. Hancock, Graph matching with a dual-step EM algorithm, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **20** (Nov. 1998), 1236–1252.

[28] T.B. Sebastian, P.N. Klein and B.B. Kimia, On aligning curves, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **25** (Jan. 2003), 116–125.