**Shape recognition of irregular objects**

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## ABSTRACT

*A new approach to object recognition is proposed. The main concern is on irregular objects which are hard to recognize even for a human. The recognition is based on the contour of an object. The contour is obtained with morphological operators and described with a Freeman chain code. The chain code histogram (CCH) is calculated from the chain code of the contour of an object. For an eight-connected chain code an eight dimensional histogram (CCH), which shows the probability of each direction, is obtained. The CCH is a translation and scale invariant shape measure. The CCH gives only an approximation of the object's shape so that similar objects can be grouped together. The discriminatory power of the CCH is demonstrated on machine-printed text and on true irregular objects. In both cases it is noted that similar objects (according to the shape of the contour) are grouped together. The results of experiments are good. It has been shown that similar objects are grouped together with the proposed method. However, the sensitivity to small rotations limits the generality of the method.*

**Keywords:** object recognition, shape analysis, irregular shape, chain code.

## 1. INTRODUCTION

It is a common problem in computer vision applications that regular or man-made objects should be recognized. For that purpose plenty of methods exist.[12,16] However, shape recognition based on the most common shape descriptors run short on irregular objects. In this paper the main concern is on irregular objects (for example surface defects) which are hard to recognize even for a human.

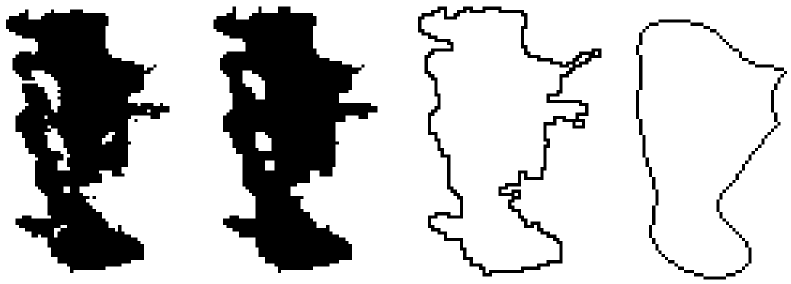
There exist several methods for the shape analysis of objects. These methods can be divided into two categories, the ones which use the whole area of an object, and the ones which use only the contour of an object. Shape descriptors that use the contour of an object include the following techniques. Moment-based techniques have been used in object recognition since 1962.[10] Moments derived from the contour of an object were used by Dubani et al.,[2] and Gupta and Srinath.[8] Zahn and Roskies[17] used the Fourier coefficients of a contour as shape descriptors. The chord distribution of a contour was proposed by Smith and Jain.[15] A scale-space technique to form a description for plane curves was proposed by Mokhtarian and Mackworth.[13] Evans et al.[3] proposed pairwise geometric histograms as shape descriptors.

The main concern in this paper is on techniques based on the Freeman chain code. The Freeman chain code[4] is a compact way to represent a contour of an object. However, the chain code has serious drawbacks when used as a shape descriptor. It is very sensitive to noise as the errors are cumulative. The starting point of the chain code, and the orientation and scale of a contour affect the chain code. The chain correlation scheme,[5] which can be used to match two chains, suffers from these drawbacks. A scheme which is invariant under scale and orientation of chains, is based on the critical points of the chains.[6,5,1] The centroidal profile[5] is a scale and orientation invariant shape descriptor. It can be calculated efficiently from the chain code of the closed plane curve by using the residue-chain length[4] instead of the Euclidean distance measure.

In this paper a new shape descriptor which is based on the Freeman chain code is proposed. The proposed shape descriptor, the chain code histogram (CCH), is defined in section two. Its properties are discussed. The discriminatory power of the chain code histogram is demonstrated on machine-printed text and on true irregular objects in section three. In section four the limitations of the chain code histogram are discussed and the conclusions are drawn.

## 2. THE PROPOSED SHAPE DESCRIPTOR

Let us suppose we have a binary image obtained from the original grey-level image by segmentation (Figure 1(a)). The defect areas are marked with black color and the non-defect areas with white color. The contour image (Figure 1(c)) is obtained by basic morphological operations.[9] Finally the contour is smoothed with the Gaussian filter[13] (Figure 1(d)). This is quite necessary because the chain code (and thus the proposed shape descriptor) is sensitive to noise. See Chapter 3.2. for a complete description of the preprocessing operations.



(a) (b) (c) (d)

Figure 1: (a) The segmented binary image, (b) the closed image, (c) the obtained contour image, and (d) the Gaussian smoothed contour image.

The Freeman chain code[4] is a compact way to represent a contour of an object. The chain code is an ordered sequence of $n$ links $\{c_i,\ i = 1, 2, ..., n\}$, where $c_i$ is a vector connecting neighboring edge pixels. The directions of $c_i$ are coded with integer values $k = 0, 1, ..., K-1$ in a counterclockwise sense starting from the direction of the positive $x$-axis (Figure 2(a)). The number of directions $K$ takes integer values $8M$ where $M$ is an integer. The chain codes where $K > 8$ are called the generalized chain codes.[7]

A new shape descriptor, the chain code histogram (CCH), is proposed. It is calculated from the chain code of a contour. The CCH is a discrete function

$$p(k) = \frac{n_k}{n} \tag{1}$$

where $n_k$ is the number of chain code values $k$ in a chain code, and $n$ is the number of links in a chain code. The CCH shows the probabilities for different directions present in a contour. A simple example is depicted in Figure 2. In Figure 2(b) is a sample object, a square. The starting point for the chain coding is marked with a black circle, and the chain coding direction is clockwise. In Figures 2(c)-(d) are the chain code and the CCH of the contour of the square.

The CCH is independent of the choice of the starting point. However, the chain coding direction (clockwise or counterclockwise) should be same for all contours. The CCH is a translation and scale invariant shape descriptor. It can be made invariant to rotations of 90° (independent of the number of directions in a chain code), because the 90° rotation causes only a circular shift in the CCH. To achieve better rotation invariance the normalized

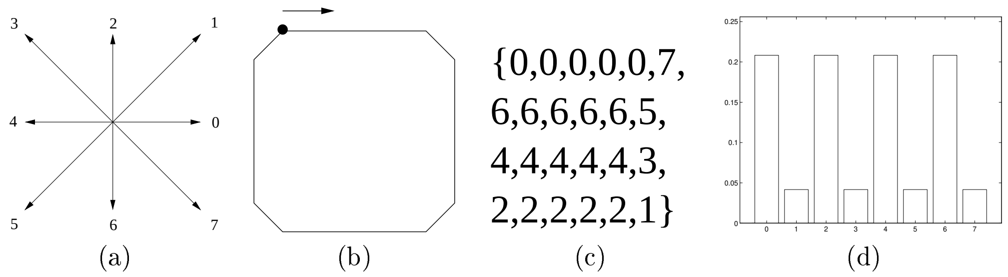



Figure 2: (a) The directions of the eight connected Freeman chain code ($K = 8$). (b) The contour of a sample object, a square, (c) chain code presentation of the square, and (d) the chain code histogram (CCH) of the square.

chain code histogram (NCCH) should be used. It differs from the CCH in that it takes into account the lengths of different directions. The NCCH is defined as

$$p_n(k) = \frac{l_k n_k}{l} \tag{2}$$

where $n_k$ is the number of chain code values $k$ in a chain code, $l_k$ is the length of the direction $k$, and $l$ is the length of the contour. For example, in case of the eight connected chain code, $l_k = 1,\ k = 0, 2, 4, 6$, and $l_k = \sqrt{2},\ k = 1, 3, 5, 7$. The NCCH can be made invariant to discrete rotations of $(360/K)^\circ$ (where $K$ is the number of directions in a chain code). By selecting a large $K$, a rotation invariance can be achieved. (In practice the digitization resolution causes some errors.)

## 3. EXPERIMENTS

The discriminatory power of the chain code histogram (CCH, Eq.1) is demonstrated on machine-printed text and on real irregular objects. In both cases we omit the inner structure of the objects, and use only information present in the contour of the objects. The experiments are concerned on grouping similar looking objects together. The sensitivity to small rotations is studied in the first experiment. The Sammon mapping is used to visualize the results.

The Sammon mapping[14] is a well-known method for visualizing the structure of high dimensional data space. It generates a mapping from a $n$-dimensional input space to a 2-dimensional plane. The mapping is nonlinear, and it tends to preserve the intersample distances, i.e., the distance between two input vectors is preserved in the mapping to two dimensions.

### 3.1. Machine-printed text

In this experiment we want to demonstrate that our shape descriptor can group together letters that look similar to a human. In Figure 3 are the contours of the 26 letters and their CCHs. The contour of each letter is chaincoded, and the CCHs are calculated. In the horizontal axis of the CCHs are the directions (an eight connected chain code is used), and in the vertical axis are the probabilities for each direction.

In Figure 4 is the Sammon mapping of the CCHs. It can be seen that similar letters are mapped close to each other, for example B, D, P, and R are grouped, as well as C, G, O, and Q. In Table 1 three closest letters for each letter are depicted. The Euclidean distance measure between the CCHs of each pair of letters is used.

The sensitivity to small rotations is then studied. The test letters were rotated 5° and 10° clockwise. In Figure

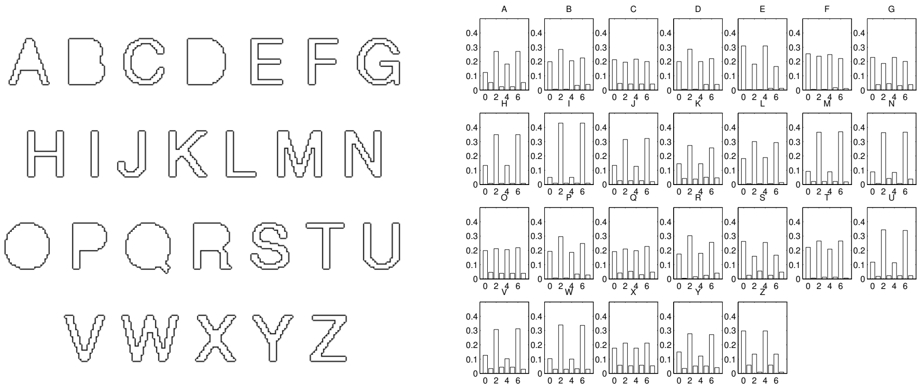


Figure 3: The contours of the 26 letters and their CCHs.

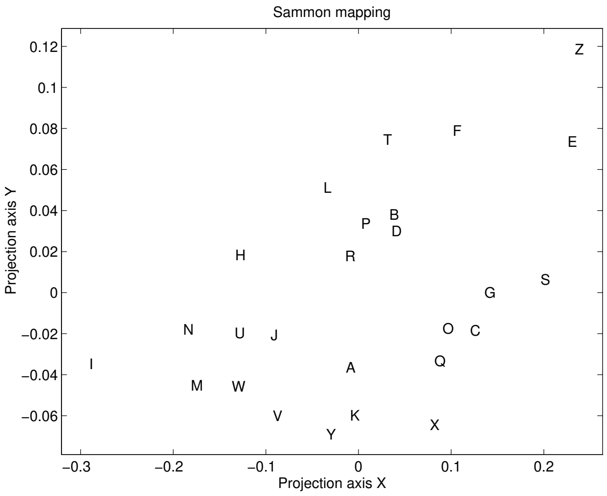
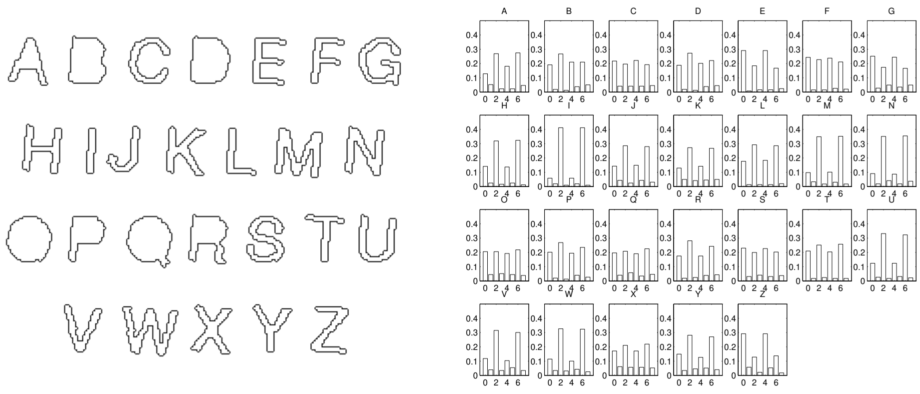



Figure 4: The Sammon mapping of the CCHs. Similar letters are mapped close to each other.

| A | B | C | D | E | F | G | H | I | J | K | L | M |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| K | D | G | B | Z | T | C | U | M | V | Y | R | N |
| R | P | O | P | S | G | O | J | N | U | A | P | W |
| Y | R | Q | R | F | B | Q | W | W | W | R | T | U |
| **N** | **O** | **P** | **Q** | **R** | **S** | **T** | **U** | **V** | **W** | **X** | **Y** | **Z** |
| M | Q | R | O | P | G | P | W | J | U | Q | K | E |
| W | C | B | X | B | C | L | H | W | M | O | V | S |
| U | X | D | C | L | E | B | J | U | V | C | J | G |

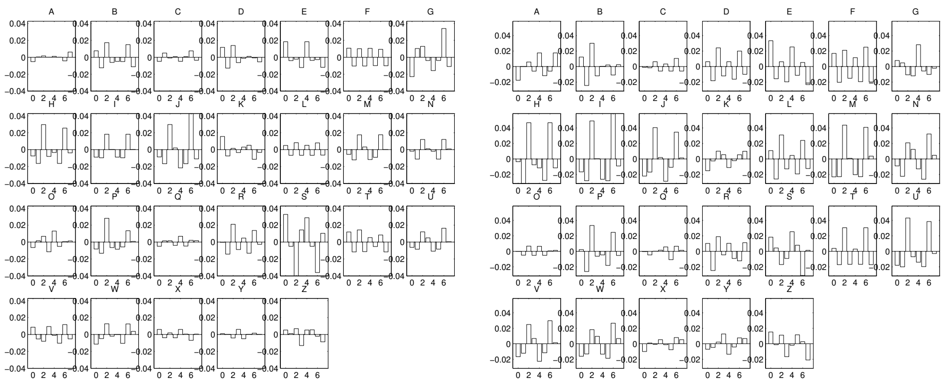
Table 1: Three closest letters for each letter (no rotation). The Euclidean distance measure is used.

5 are the contours of the 26 letters after the 5° rotation clockwise and their CCHs. In Figure 6 are the differences between the CCHs of letters with no rotation and 5° rotation, and with no rotation and 10° rotation. There are noticeable changes within some letters. In Figure 7 is the Sammon mapping of the CCHs of the unrotated and rotated letters.



(a) (b)

Figure 5: (a) The contours of the 26 letters after the 5° rotation clockwise and (b) their CCHs.



(a) (b)

Figure 6: The differences between the CCHs of letters with (c) no rotation and 5° rotation, and with (d) no rotation and 10° rotation.

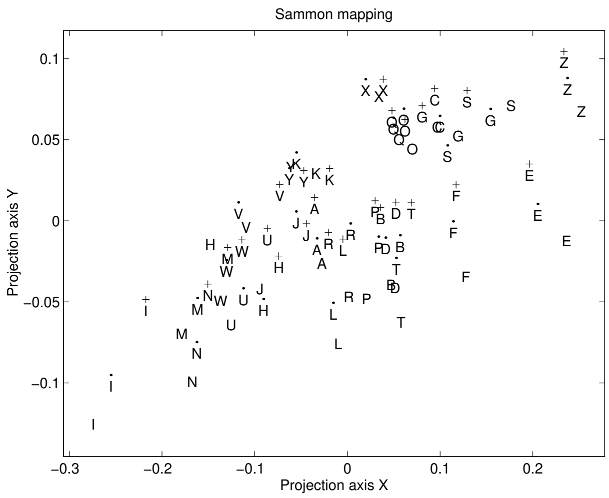



Figure 7: The Sammon mapping of the CCHs of the letters with different rotations. Plain letters are with rotation angle 0°, letters with a spot are with rotation angle 5°, and letters with a plus are with rotation angle 10°.

### 3.2. Real irregular objects

The discriminatory power of the CCH is demonstrated on real irregular objects. These objects are surface defects which are obtained from base paper samples via an unsupervised segmentation procedure.[11] An example defect is depicted in Figure 1(a). The defect areas are marked with black color and the non-defect areas with white color. The basic morphological operations,[9] erosion and dilation, are used in processing the image. A 3x3 structuring element is used. To fill up small holes and gulfs present in the binary image a morphological closing operation (dilation followed by erosion) is applied to the image (Figure 1(b)). The contour image in Figure 1(c) is obtained by subtracting the closed image from the dilated image. Thus the obtained contour is larger than the true contour. Finally the contour is smoothed with the Gaussian filter[13] (Figure 1(d)).

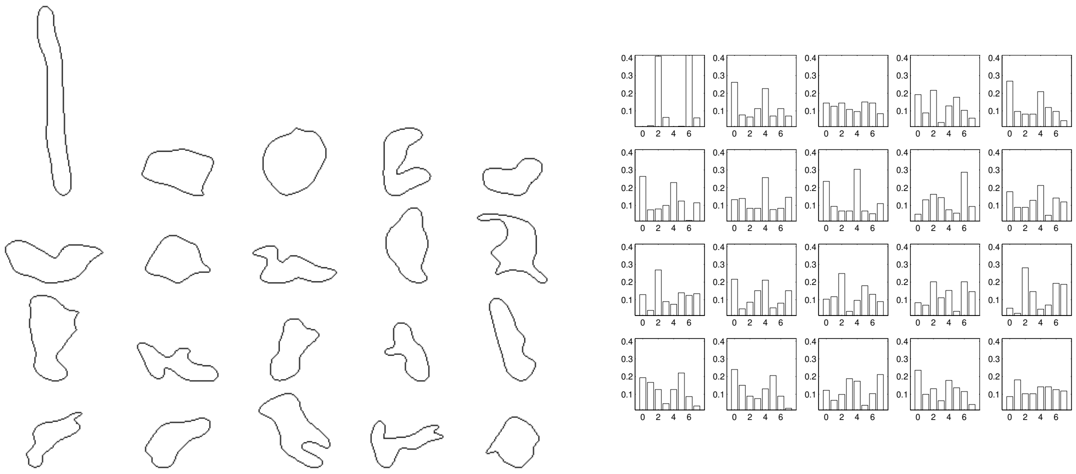


Figure 8: The contours of the 20 real irregular objects and their CCHs.

A set of 20 surface defects were used in the experiment. The contours of the surface defects and their CCHs are depicted in Figure 8. The eight connected chain code is used. In Figure 9 is the Sammon mapping of the CCHs. It can be seen that similar looking objects are mapped close to each other. The horizontally oriented objects are at the bottom, the circular objects in the center, and the vertically oriented objects in the top. The ordering of objects (based on the shape of their contours) is good.

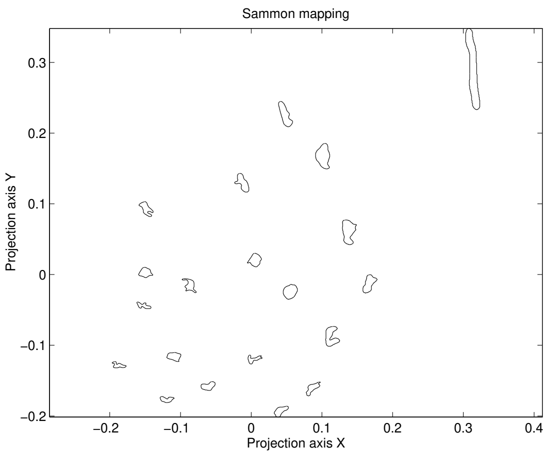



Figure 9: The Sammon mapping of the CCHs of the real irregular objects.

## 4. DISCUSSION AND CONCLUSIONS

This study concentrates on fractal-kind, irregular objects (like the one in Figure 1(a)), which can be obtained from various processes by segmentation. Surface defects in web and strip products (metal, paper, textiles, non-wowens, plastic film, etc.) are good examples of such objects. They do not necessary possess any characteristic shape or structure. The contour of such object can be very uneven, fractal-kind. The preprocessing of a contour is necessary before any shape analysis can be made. In this study a smooth approximation of a contour is used. It is obtained by smoothing a contour with the Gaussian filter. A contour $C$ can be presented in terms of two periodic functions $x(t)$ and $y(t)$, $C = \{x(t), y(t)\}$, where $t$ is a linear function of the path lenght. These functions are convolved with a one-dimensional Gaussian filter to produce a smoothed contour. The inner structure of an object is not considered here, although it is quite evident that it can have useful information on an object. For example, the number of different regions (holes, non-defect areas, etc.), the textural properties (average gray level value, smoothness, edgeness, etc.) and the shapes of these regions may be of interest.

The chain code histogram is meant to group together objects that look similar to a human. It cannot preserve information on the exact shape of a contour of an object, because it only shows the probabilities for the different directions present in a contour. Thus there may be many objects with the same chain code histogram. For example, in Figure 10 is a simple convex object. If the top of the object is mirrored down, a concave object, which is very different from the original one, is obtained. The chain codes for the objects are different. However, the chain code histograms are identical for both objects.

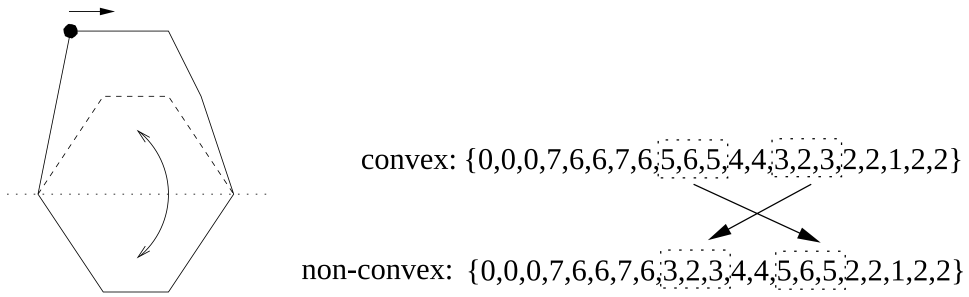



Figure 10: The chain code histograms are identical for the original convex object and the mirrored concave object although the chain codes are different.

The proposed shape measure, the chain code histogram, is a statistical measure for the directionality of the contour of an object. The chain code histogram is a translation and scale invariant shape descriptor, and it is independent of the choice of the starting point for the chain coding. The calculation of the chain code histogram is fast and simple. The chain code histogram is not meant for exact detection and classification tasks, but to group together objects that look similar to a human. The results of experiments with machine-printed text and with true irregular objects are good. It has been shown that similar objects are grouped together. However, the sensitivity to small rotations limits the generality of the proposed shape descriptor.

## 5. ACKNOWLEDGMENTS

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