I (14):	
II (20):	
III (16):	

Schriftliche Prüfung aus Grundlagen der Digitalen Bildverarbeitung WS 2010/2012

Walter G. Kropatsch, Nicole M. Artner

Bitte tragen Sie Ihre Matrikelnummer, Ihren Namen und Ihre Studienkennzahl in die dafür vorgesehenen Kästchen ein:

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Diese Prüfung besteht aus drei Teilen auf die Sie insgesamt 50 Punkte erreichen können. Für besonders gute Begründungen können Zusatzpunkte erreicht werden. Die Dauer der Prüfung beträgt 90 Minuten. Schriftliche Unterlagen (Skriptum, Buch, etc.) sind zugelassen. Es gilt der folgende Notenschlüssel:

Note:	1	2	3	4	5
Punkte:	> 42	37:42	31:36	25:30	0:24

Teil I: Interpretation von Bildoperationen (14)

Im ersten Teiles sollen Sie Ergebnisbilder über vorgegebene Operationen mit den gegebenen Eingabebildern in Beziehung setzen. Auf den folgenden 2 Seiten finden Sie 24 Bilder die als Eingabe als auch als Ergebnis einer Bildoperation auftreten können. Beachten Sie, dass nicht ALLE Bilder verwendet werden, es kann Bilder geben, die nicht als Eingabe- oder Ergebnisbilder aufscheinen.

Allgemeines

Die angegebenen Bilder haben eine Größe von 350x350 Pixeln. Grauwertbilder haben einen Wertebereich von 0 bis 255 (falls nicht anders angegeben). Logische Operationen werden im Rahmen der Prüfung nur auf Binärbilder (Schwarz-Weiss-Bilder) angewendet. `true` wird durch den Wert 1 (=weiss) repräsentiert, `false` durch den Wert 0 (=schwarz).

Matlab Referenz

Notationen

Matrix $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$ `A=[a b; c d]`; *Spaltenvektor* $x = \begin{pmatrix} y \\ z \end{pmatrix}$ `x=[y;z]`

Zeilenvektor $e = \begin{pmatrix} f & g \end{pmatrix}$ `e=[f g]`

Command Reference

`Y = abs(X)`
returns an array Y such that each element of Y is the absolute value of the corresponding element of X.

`C=conv2(A,B)`
computes the two-dimensional convolution of matrices A and B.

`BW = edge(I,'canny',thresh,sigma)`
specifies sensitivity thresholds for the Canny method. thresh is a two-element vector in which the first element is the low threshold, and the second element is the high threshold. sigma is the standard deviation of the Gaussian filter.

`Y = fft2(X)`
returns the two-dimensional discrete Fourier transform (DFT) of X, computed with a fast Fourier transform (FFT) algorithm.

`Y = fftshift(X)`
rearranges the outputs of fft, fft2, and fftn by moving the zero-frequency component to the center of the array.

`h = fspecial('gaussian',hsize,sigma)`
returns a rotationally symmetric Gaussian lowpass filter of size hsize with standard deviation sigma (positive). hsize can be a vector specifying the number of rows and columns in h

`BW = im2bw(I,level)`
converts the intensity image I to black and white. The output binary image BW has values of 0 for all pixels in the input image with luminance g less than *level* and 1 for all other pixels:

$$bw = 0 \Leftrightarrow \frac{g - g_{min}}{g_{max} - g_{min}} < level$$

`IM2 = imdilate(IM,SE)`
dilates the grayscale, binary, or packed binary image IM, returning the dilated image, IM2. The argument SE is a structuring element object.

`IM2 = imopen(IM,SE)`
performs morphological opening on the grayscale or binary image IM with the structuring element SE. The argument SE must be a single structuring element object.

`y = log1p(x)`
computes log(1+x), compensating for the roundoff in 1+x.

`B = medfilt2(A)`
performs median filtering of the matrix A using the default 3-by-3 neighborhood.

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Folgende Liste enthält 10 Bildoperationen, die auf eines oder mehrere (z.B. $Y+Z$) der Bilder A-X angewandt wurden und eines der Bilder A-X als Ergebnis haben. Ihre Aufgabe ist die Rekonstruktion dieser 10 Bildoperationen. Tragen Sie bitte die Bildnamen (`A-X`) in die Kästchen ☐ der jeweiligen Operation ein. Jede korrekte Antwort wird mit einem Punkt belohnt. Für jene 4 Antworten, die den ersten vier verschiedenen Ziffern Ihrer Matrikelnummer entsprechen (sollten nur 3 verschiedene Ziffern auftreten, so wird durch "4" ergänzt), gibt es einen Punkt zusätzlich für eine korrekte Antwort und einen Abzugspunkt für eine falsche Antwort. Für entsprechend gute und korrekte Begründungen kann es Zusatzpunkte geben, die Verluste in anderen Abschnitten ausgleichen können!

0. ☐ `= medfilt2(N);`

   Begründung: ....

1. ☐ `= conv2(N, fspecial('gaussian',[10 10],4);`

   Begründung: ....

2. ☐ `= conv2(` ☐ `,[-2 -1 0; -1 0 1; 0 1 2]);`

   Begründung: ....

3. ☐ `= conv2(` ☐ `,[0 -1 -2; 1 0 -1; 2 1 0]);`

   Begründung: ....

4. ☐ `= edge(` ☐ `,'canny',[0.2 0.5],1);`

   Begründung: ....

5. ☐ `= im2bw(` ☐ `,35/255);`

   Begründung: ....

6. ☐ `= imopen(` ☐ `,strel('disk',3));`

   Begründung: ....

7. ☐ `= imdilate(` ☐ `,strel('disk',10));`

   Begründung: ....

8. ☐ `= "Hough-Transform"(` ☐ `);`

   Begründung: ....

9. ☐ `= log1p(abs(fftshift(fft2(O))));`

   Begründung: ....

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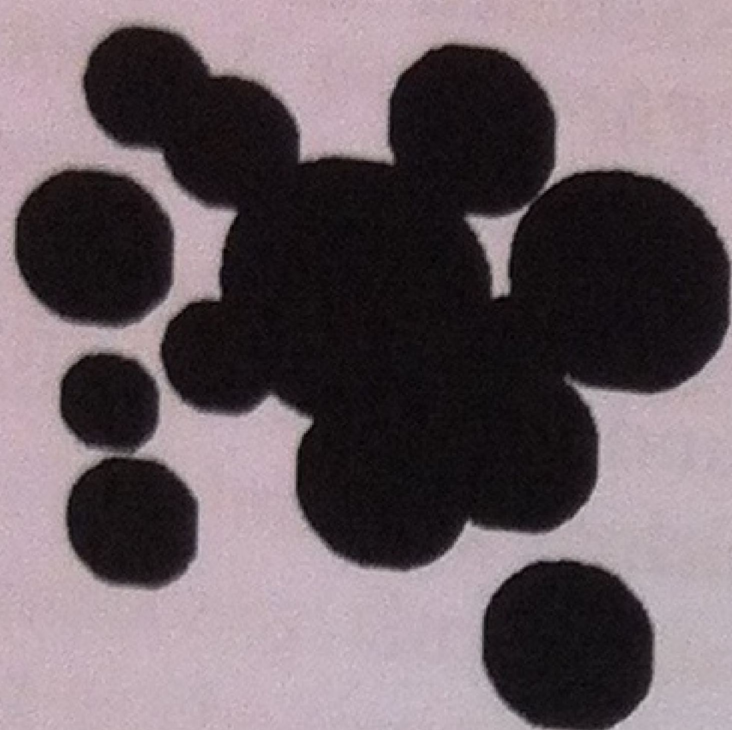
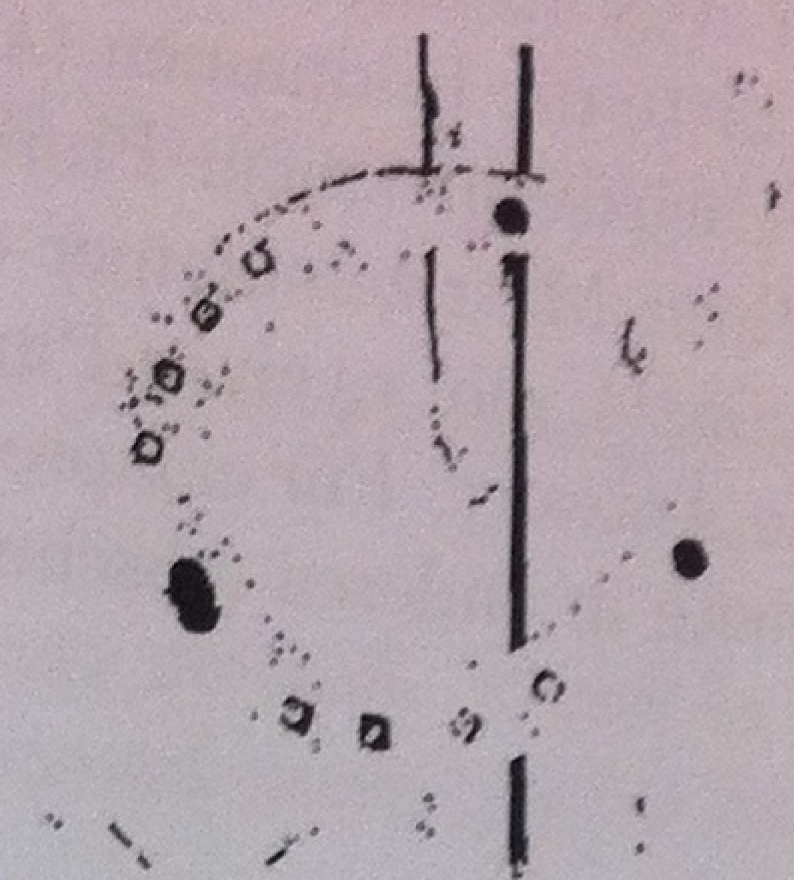
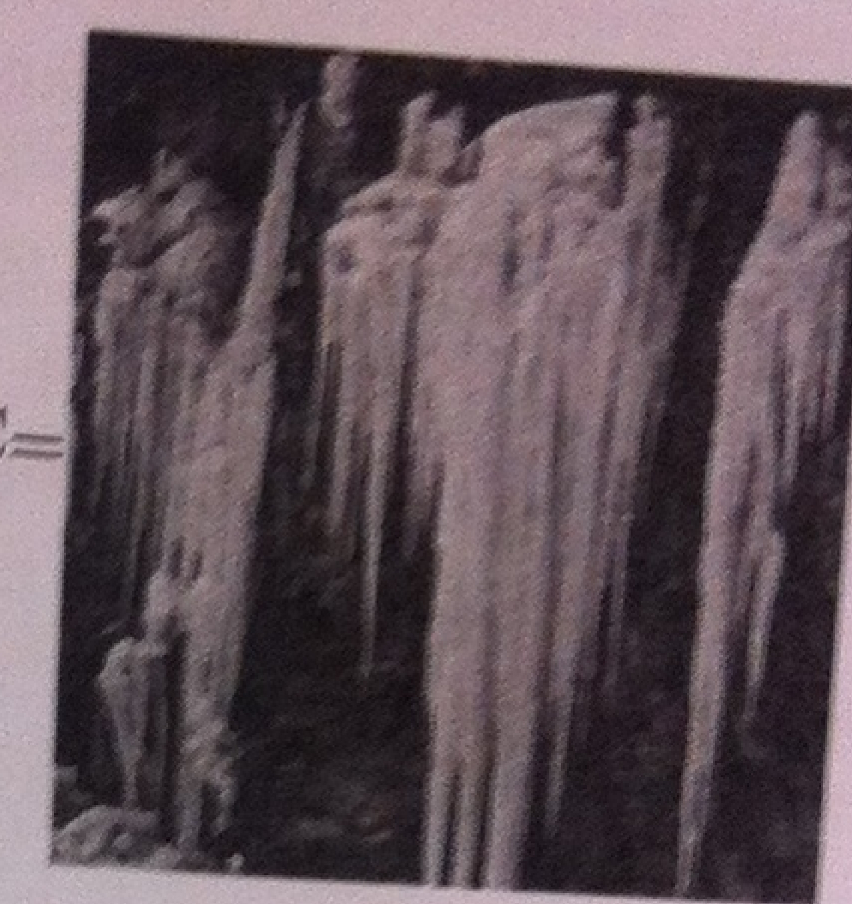
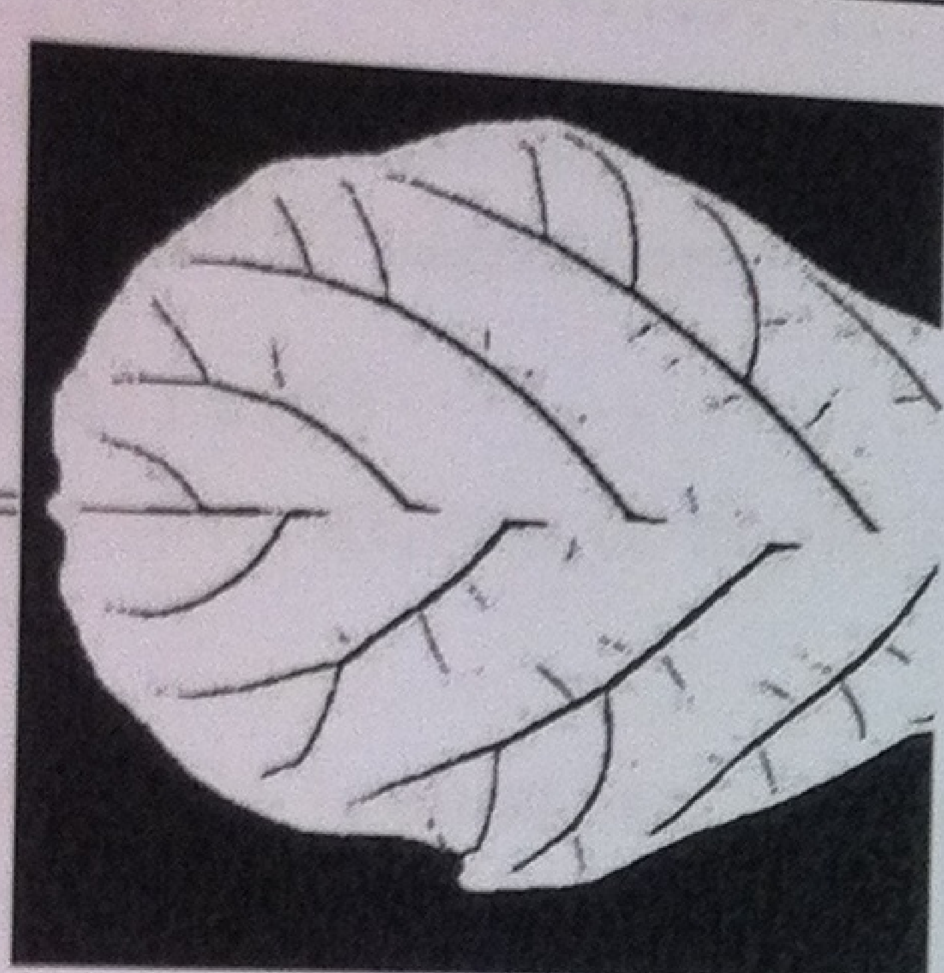
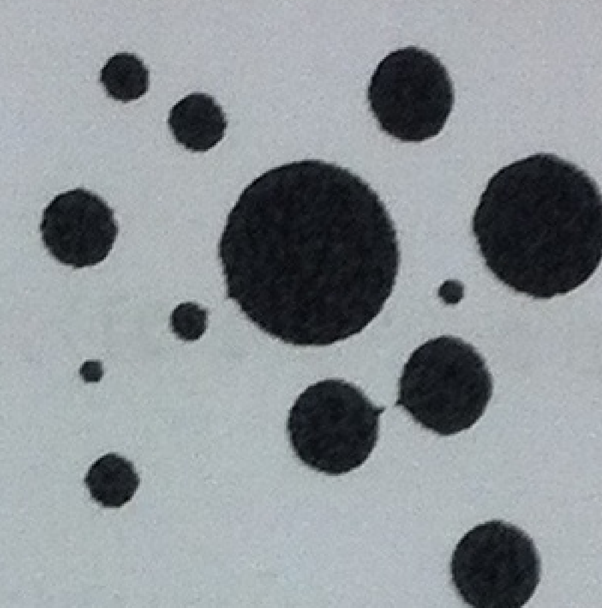
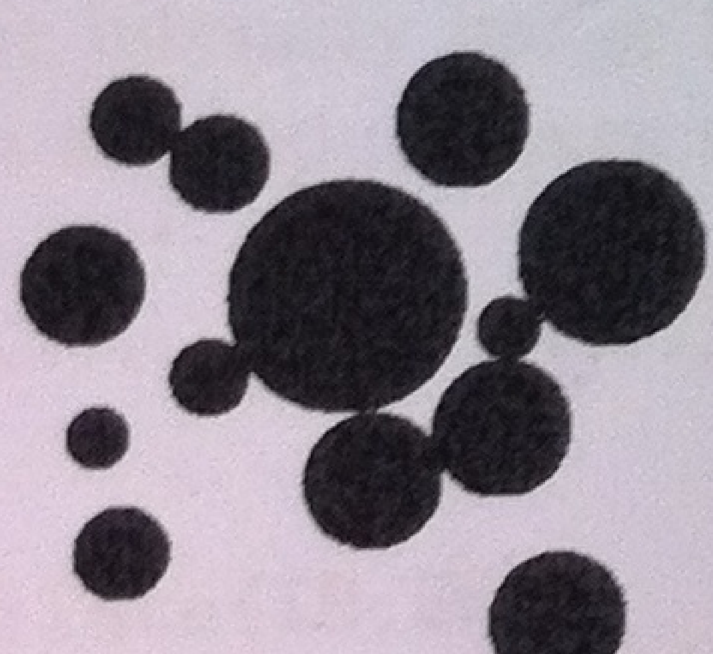
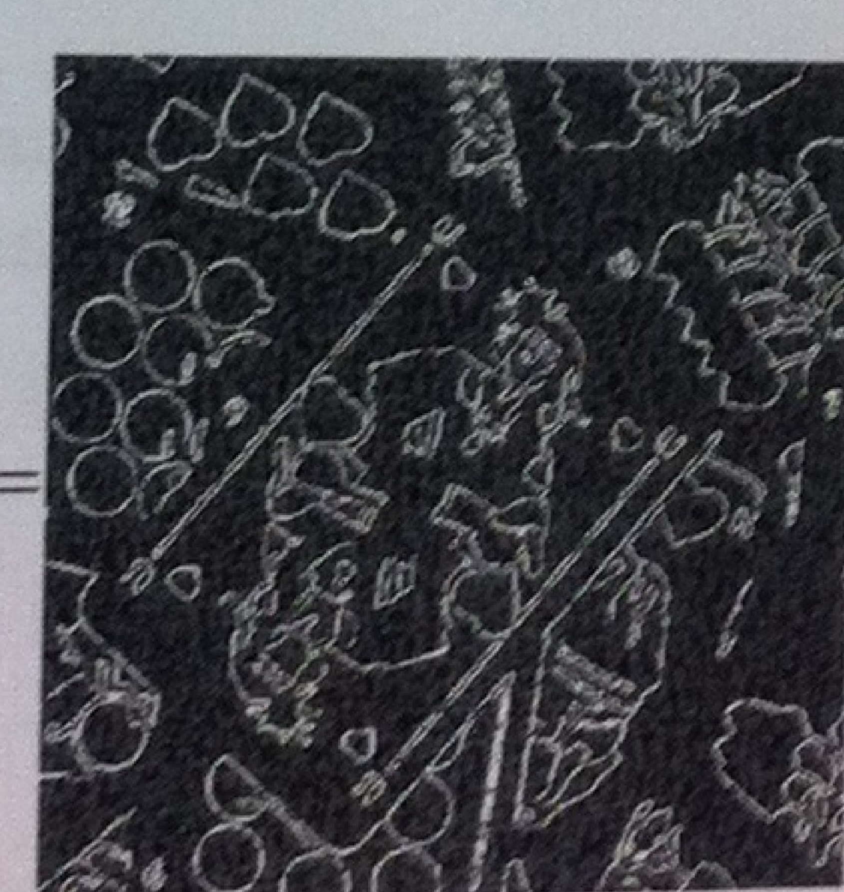
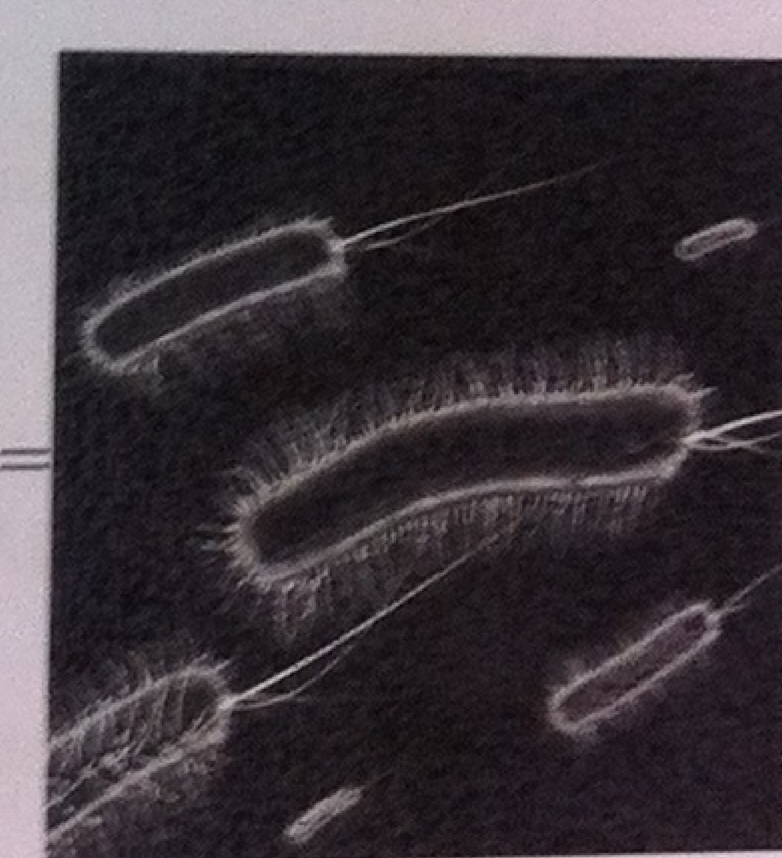
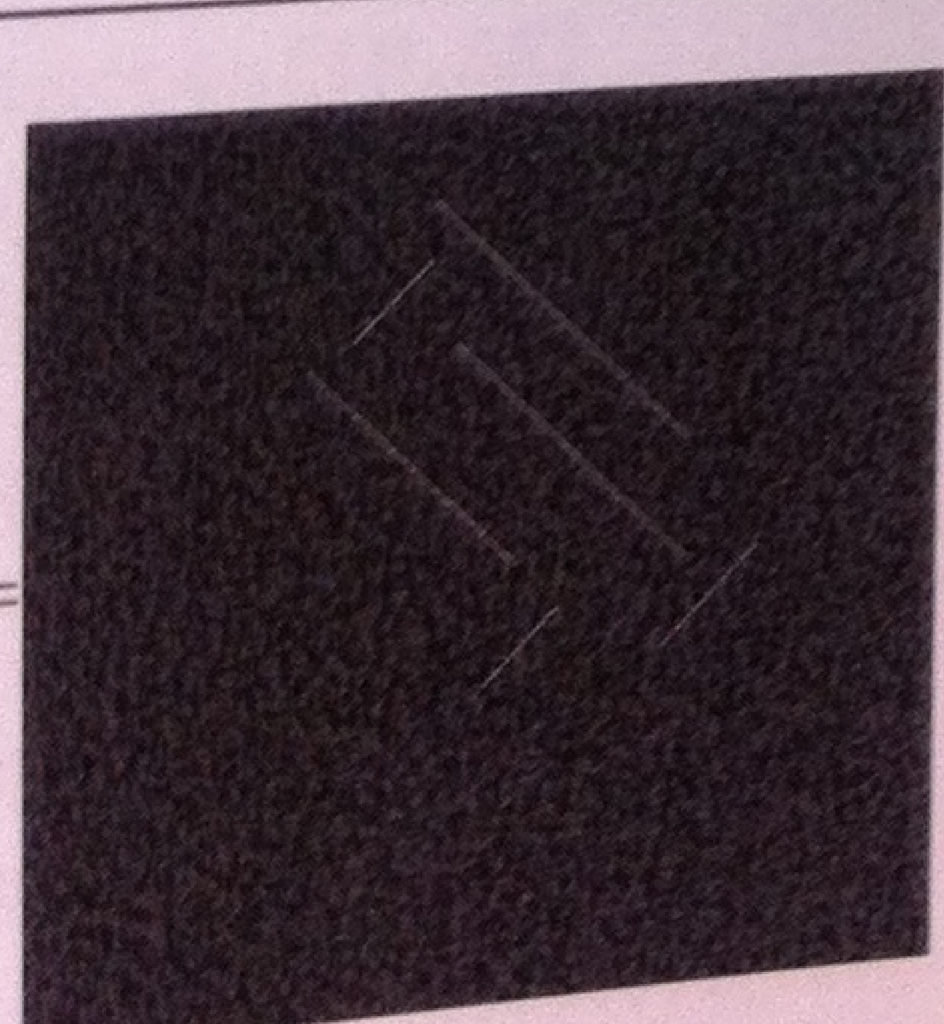
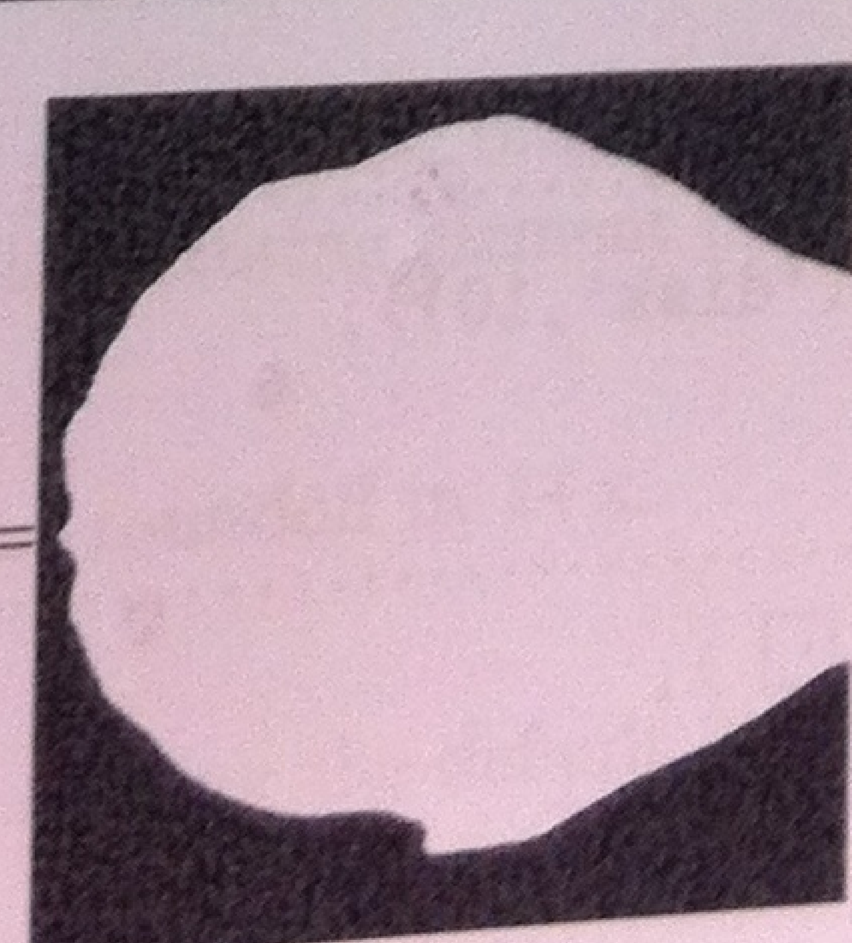
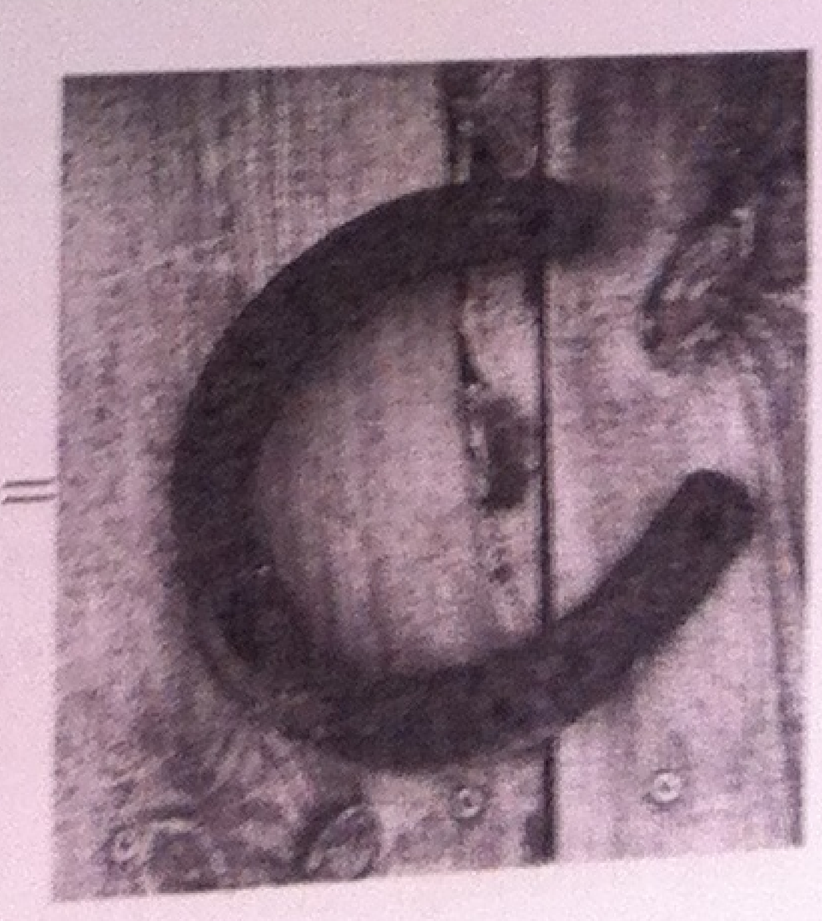
Binärbilder		Grauwertbilder
A= 	B= 	C= 
D= 	E= 	F= 
G= 	H= 	I= 
J= 	K= 	L= 

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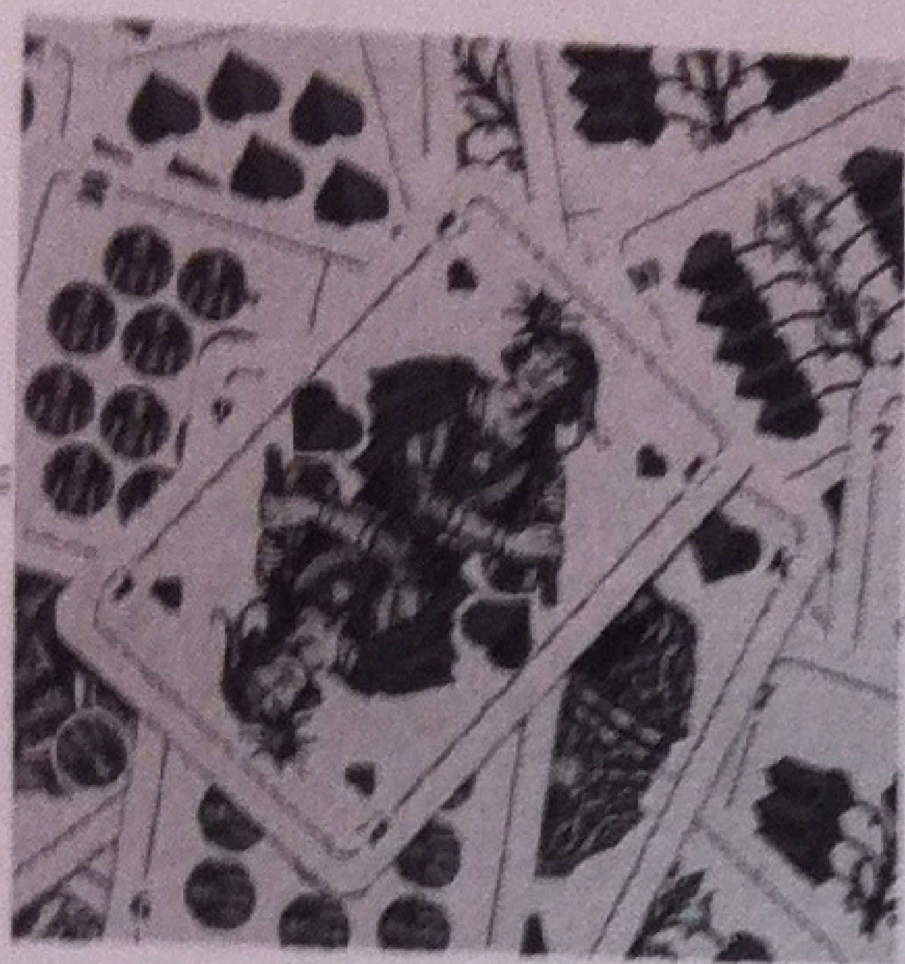
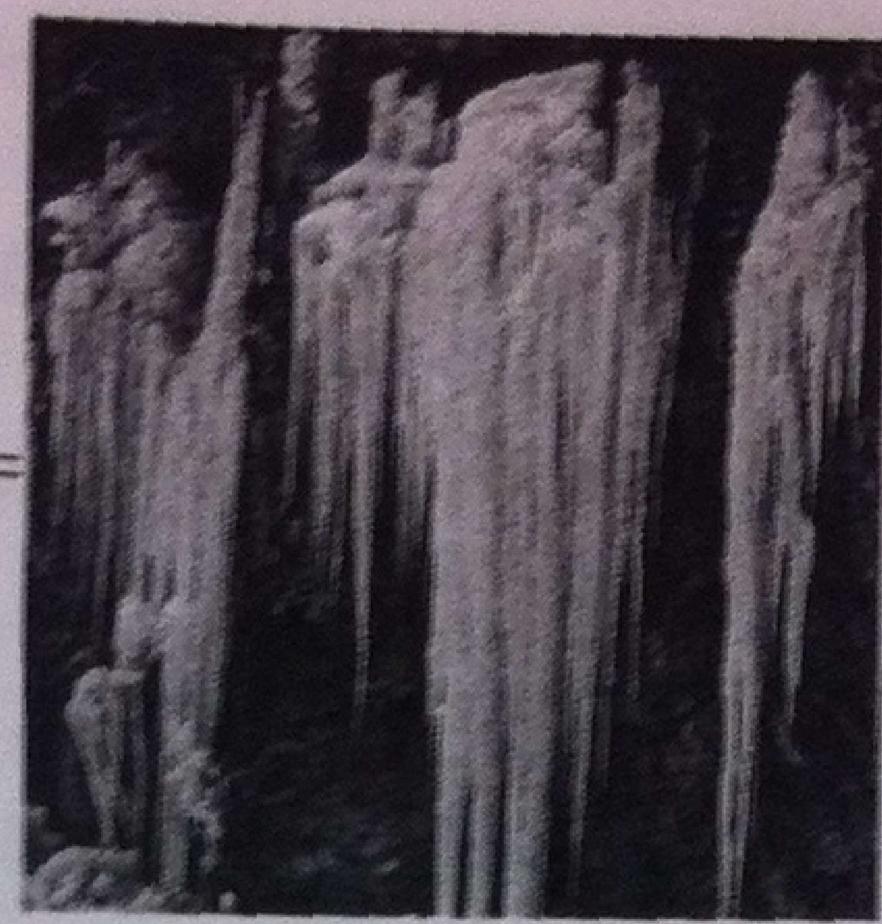
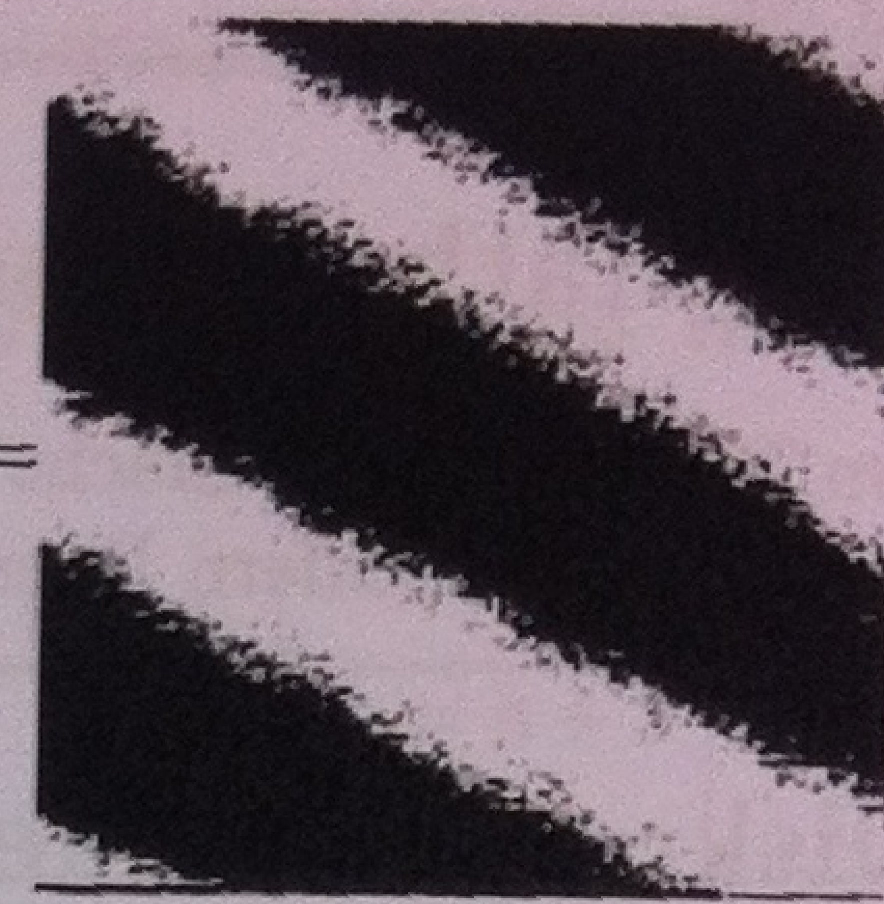
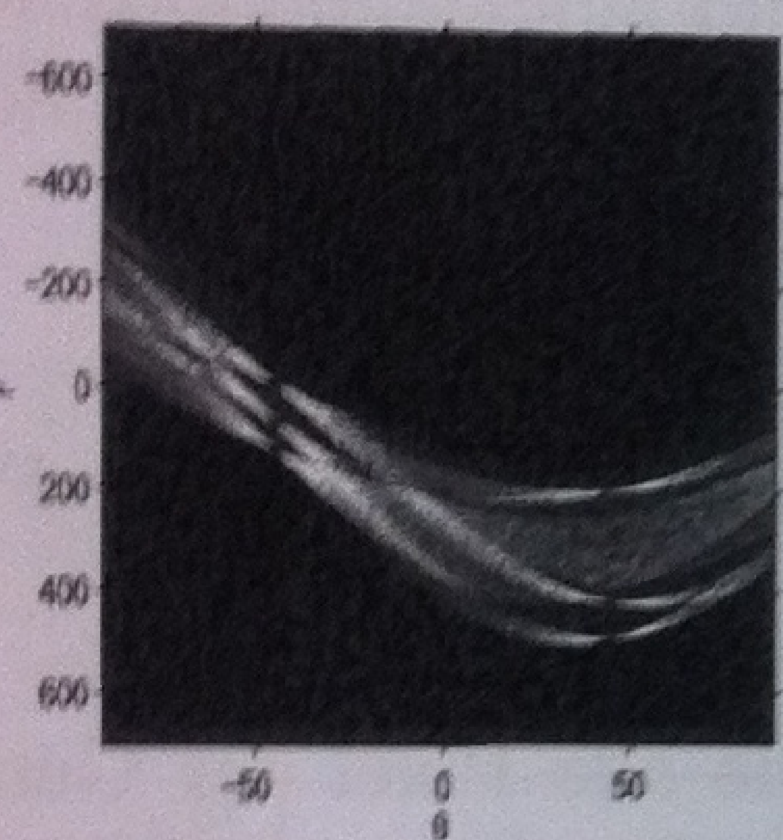
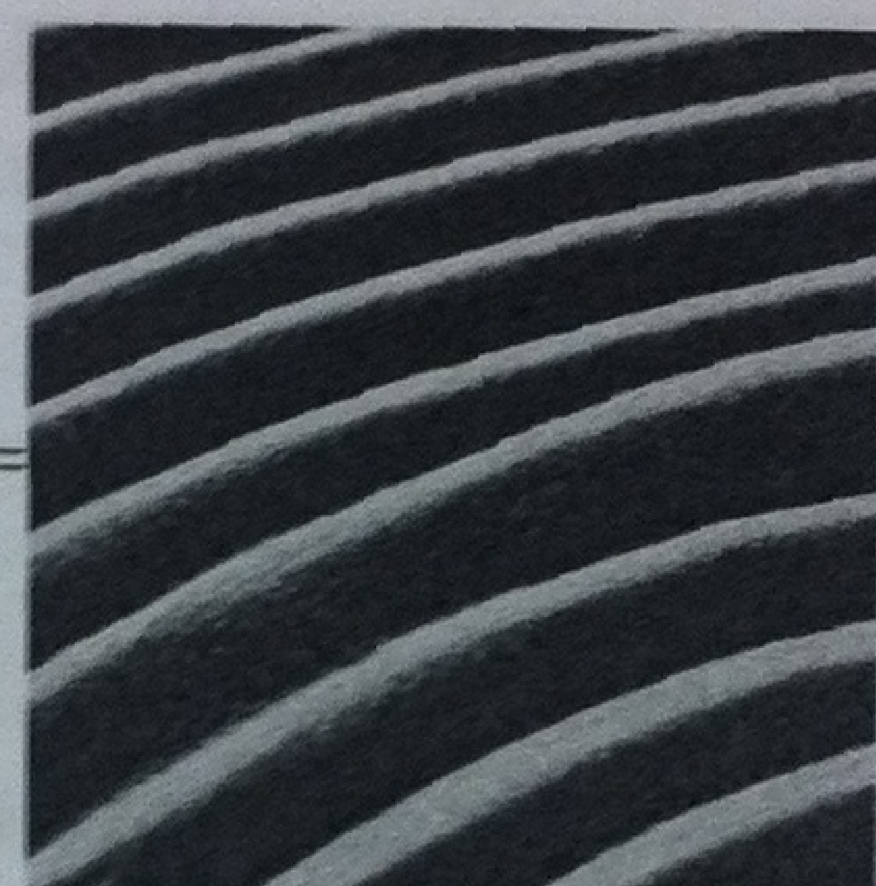
Grauwertbilder

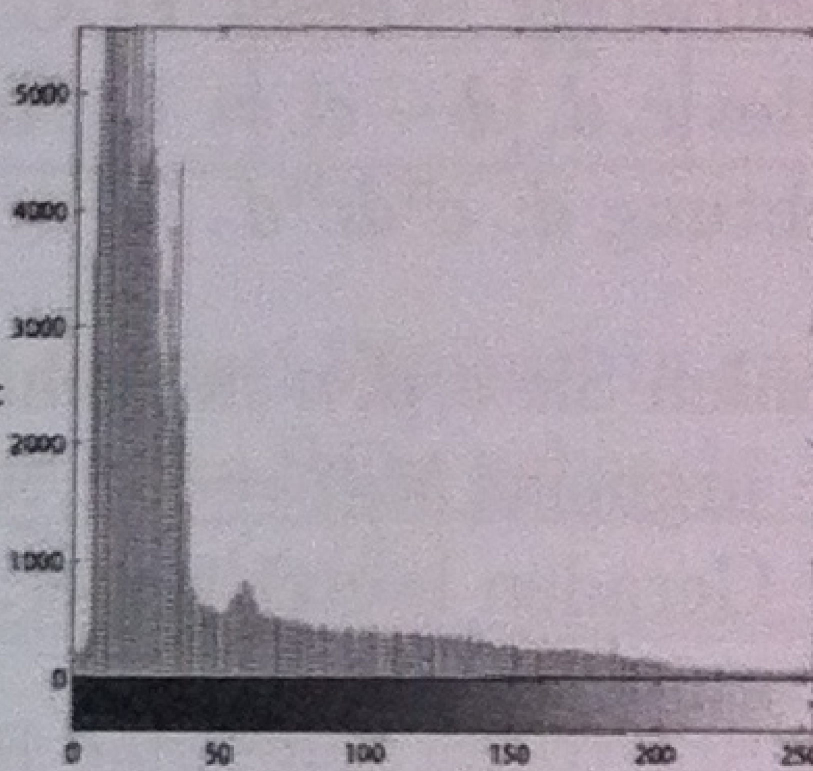
M= 

N= 

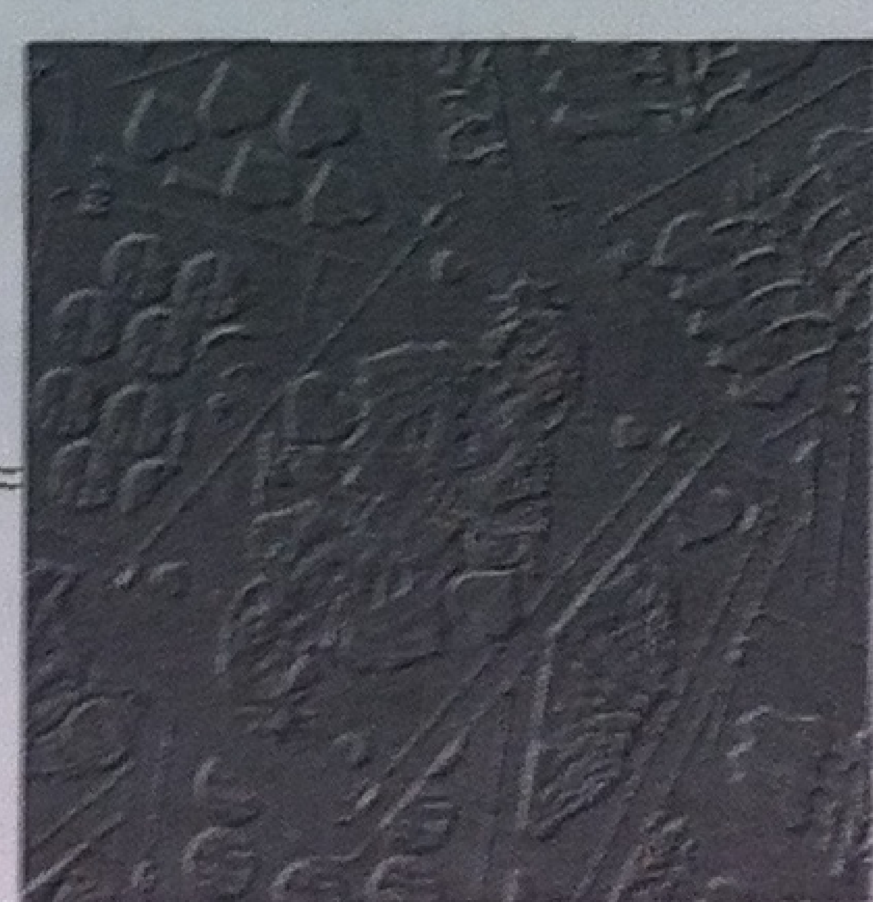
O= 

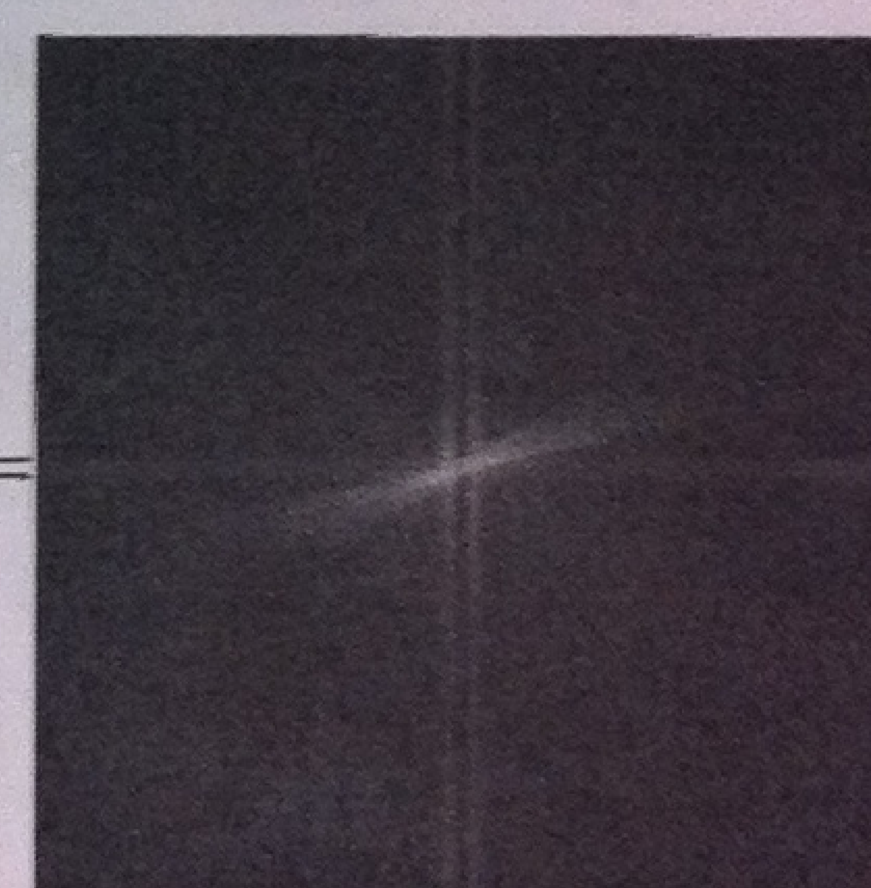
P= 

Q= 

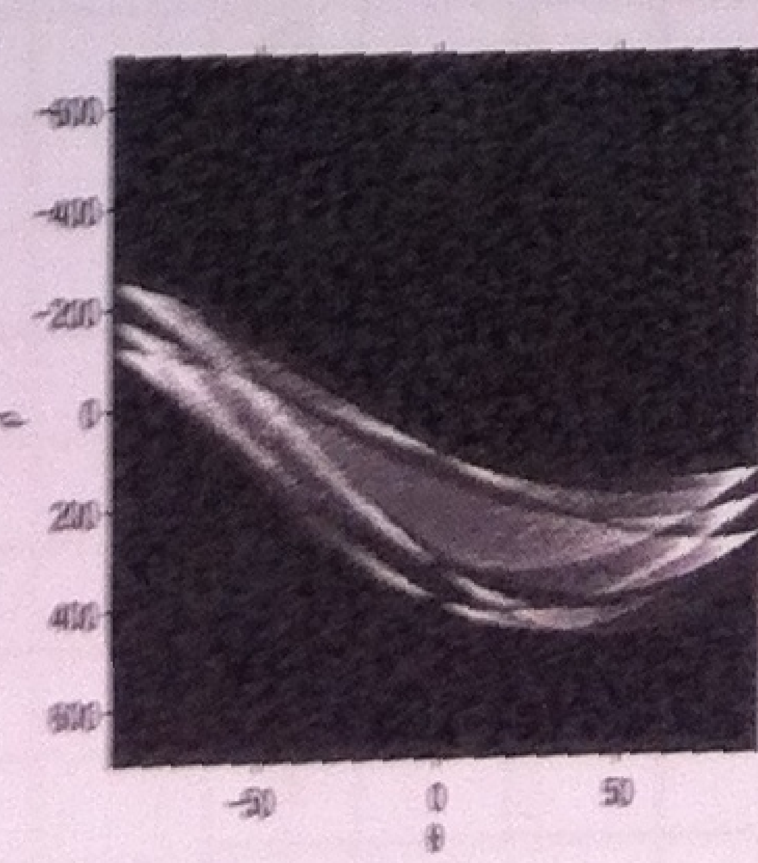
R= 

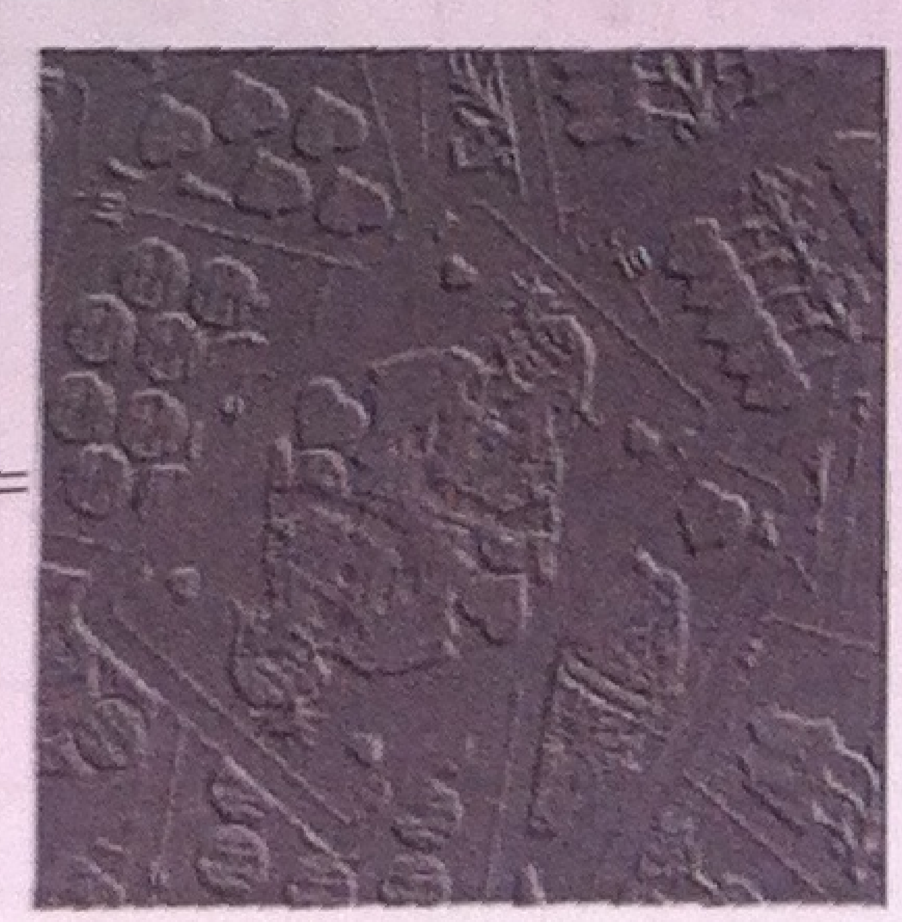
S= 

T= 

U= 

V= 

W= 

X= 

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Teil II: Mathematisches Nachvollziehen (20)

In diesem Teil sollen Sie einfache Bildverarbeitungsoperationen numerisch nachvollziehen. Bezeichne $M_1, M_2, \ldots M_7$ die 7 Ziffern Ihrer Matrikelnummer M.

1 Diskrete Geraden und Morphologie (5)

08XXXXX
↓
2

1. Diskrete Geraden entstehen durch Abtastung und werden mit Freeman Chain Codes (FCC) beschrieben. Dieser FCC besteht aus maximal zwei verschiedenen und aufeinanderfolgenden Codes $c, d, |d-c| = 1$. Nur der Code c kann wiederholt auftreten, danach folgt eine Stufe in Richtung d: $c^n d c^n d \ldots$.

2. Wählen Sie c, d, n in Abhängigkeit der Ziffern Ihrer Matrikelnummer M wie folgt: $d = \text{argmax}\{M_i | i = 1, 2, \ldots 7\} = \boxed{2}$, $c = d - 1 = \boxed{1}$, $n = \max\{2, c-2\} = \boxed{2}$. Der FCC der Geraden lautet daher: (.... $1^2 2 1^2 2$ ...)*.

3. Als Startpixel wird der Bildmittelpunkt (6,6) gewählt. Markieren Sie alle Pixel der Gerade $c^n d c^n d \ldots$ durch $\circ$, wobei **zyklischer Abschluss** angenommen wird. Das heisst die Gerade wird am jeweils gegenüberliegenden Bildrand fortgesetzt bis jener Quadrant des Bildes erreicht ist, in den die Gerade startete. Das Binärbild $B = \{\circ\}$ inkludiert alle Pixel der Gerade und auch die vorgegebenen 2 Störpixel.

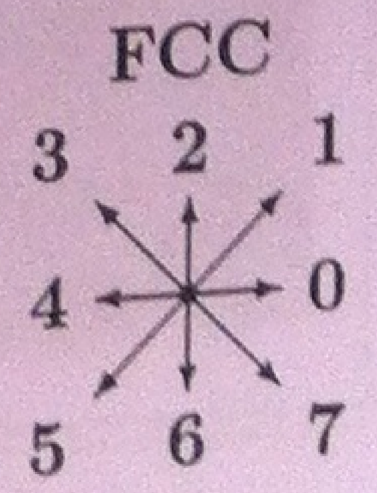
4. Mit welchem morphologischen Operator und welchem Strukturelement (SE) werden die 1.Pixel der Läufe c^n erkannt? $B_1 = \{\bullet\} = \boxed{}(B, SE)$. Markiere die erkannten Stufenpixel mit $\bullet$.

$B =$

$y=12$			•				•				o		
$y=11$		•				o					•		
$y=10$	o					•				•			
$y=9$	•				•				o				
$y=8$				o					•				•
$y=7$				•				•				•	
$y=6$			•				o					•	
$y=5$		o					•				•		
$y=4$		•		o		•				o	o		
$y=3$	•				o					•			o
$y=2$					•			o	•				•
$y=1$				•				•				•	
$y=0$			o										
$x=$	0	1	2	3	4	5	6	7	8	9	10	11	12

$SE =$

			•		
		•			



2 Hough-Transformation (5)

1. Zwei Parameter bestimmen den Hough-Akkumulator: $a = 10 - \min\{M_i | i = 3, \ldots, 7\} = \square$, $b = 3 + \text{argmax}\{M_i | i = 2, \ldots, 6\} = \square$.

2. Im Hough-Akkumulator werden die drei Winkel $\theta \in \{0^0, 90^0, 135^0\}$ und pro Winkel drei Abstände $r = r_1, r_2, r_3$ und die 4 Intervalle dazwischen gezählt:

	$r < r_1$	r_1	$r_1 < r < r_2$	r_2	$r_2 < r < r_3$	r_3	$r_3 < r$
$\theta = 0^0$		$r_1 = 1$		$r_2 = a$		$r_3 = a + 3$	
$H(0^0, r) =$	0	b	3	$b + 1$	3	b	0
$\theta = 90^0$		$r_1 = 1$		$r_2 = 4$		$r_3 = b + 3$	
$H(90^0, r) =$	0	a	3	$a + 1$	3	a	0
$\theta = 135^0$		$r_1 = \frac{1-a}{\sqrt{2}}$		$r_2 = 0$		$r_3 = \frac{b-1}{\sqrt{2}}$	
$H(135^0, r) =$	0	4	3	5	3	4	0

3. Die Hesse'schen Normalform $\boxed{r = \qquad}$ lässt sich für die drei Winkel[1] in ganzzahligen Koordinaten ausdrücken, wenn die Terme mit x und y auf die linke Seite gebracht werden:

θ	$f(x, y)$	$=$	$g(r_1(\theta))$	$g(r_2(\theta))$	$g(r_3(\theta))$
0^0		$=$			
90^0		$=$			
135^0		$=$			

4. Jedes Element $H(\theta, r)$ entspricht der Anzahl von Pixel auf der durch θ und r bestimmten Geraden, kann also als 'Projektion' entlang der Gerade gedeutet werden. Ihre Aufgabe ist die Umkehr dieser Projektion (auch diskrete Tomographie genannt), wobei als Ergebnis das Binärbild gesucht ist, dessen Houghtransformation oben spezifiziert ist. Tipp: Ist $H(\theta, r) = 0$ so sind alle Pixel dieser Gerade 0. Gibt es genau n Elemente einer Geraden, die nicht Null sind und $H(\theta, r) = n$, dann sind alle fehlenden Pixel dieser Gerade 1.

$y = 12$														
$y = 11$														
$y = 10$														
$y = 9$														
$y = 8$														
$y = 7$														
$y = 6$														
$y = 5$														
$y = 4$														
$y = 3$														
$y = 2$														
$y = 1$														
$y = 0$														
$x =$	0	1	2	3	4	5	6	7	8	9	10	11	12	13

[1] $\sin 135^o = 1/\sqrt{2}$

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3 3×3 Minimumpyramide (5 P)

1. Die Häufigkeit der Grauwerte 0 bis 7 der Grundebene Min_0 wird durch Ziffern Ihrer Matrikelnummer bestimmt: $H_0(0) = M_1, H_0(g) = M_g, g = 2, 3, \ldots 7$. Der Rest der 7×7-Grundebene ist mit dem Grauwert 1 aufgefüllt.

$g =$	0	1	2	3	4	5	6	7
$H_0(g) =$								
$K_0(g) =$								49
$H_1(g) =$								

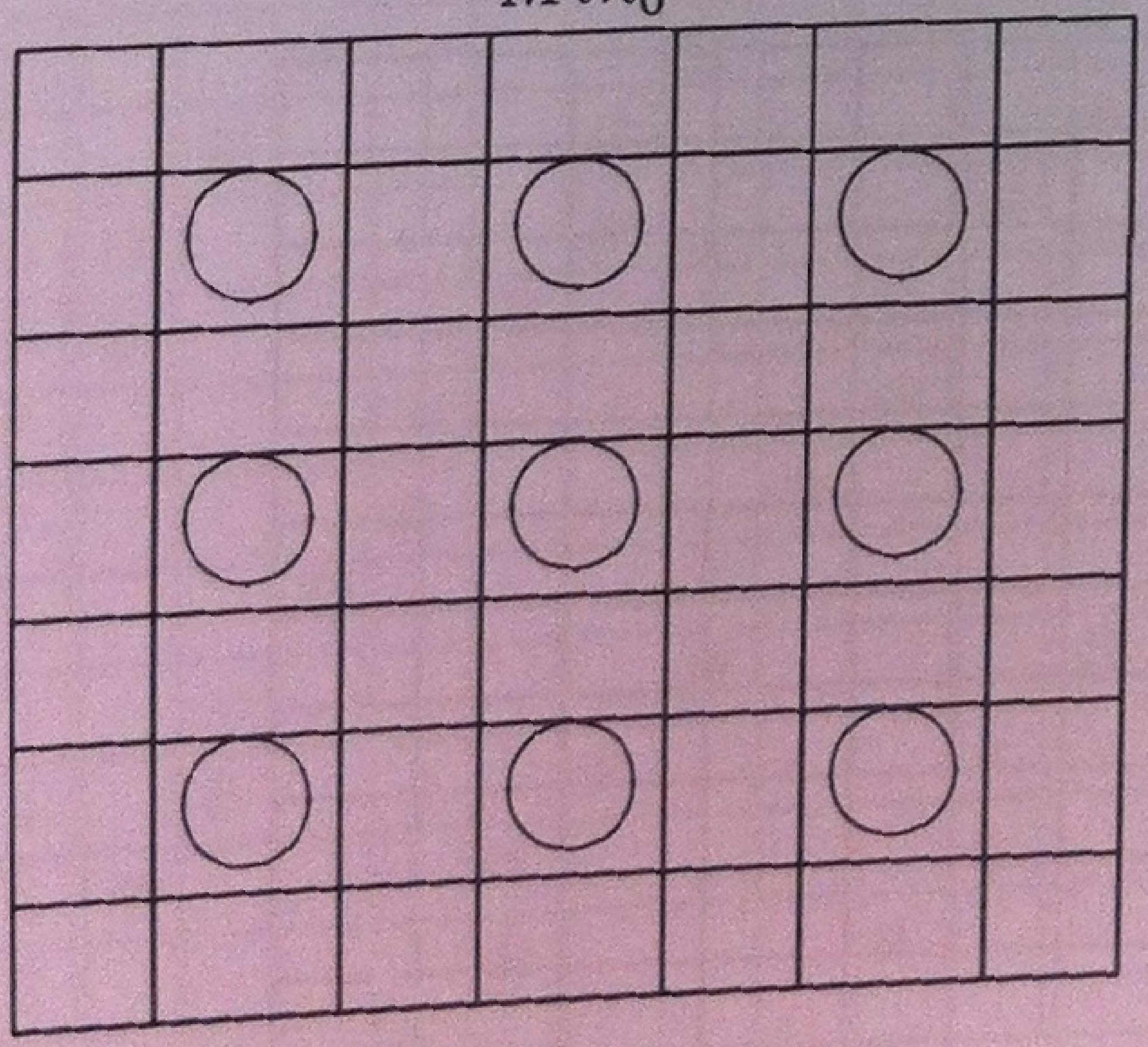
2. Bestimme das kumulative Histogramm $K_0(g) = \sum_{i=0}^{g} H_0(i)$.

3. Das Histogramm der Ebene 1 der $3 \times 3/4$ Minianpyramide wird durch $H_1(g) \approx [H_0(g)/5]$ ermittelt, wobei 'Ziel gerichtet' gerundet wird: Minima müssen erhalten bleiben und die Gesamtpixelanzahl der Ebene 1 muss genau 9 sein!

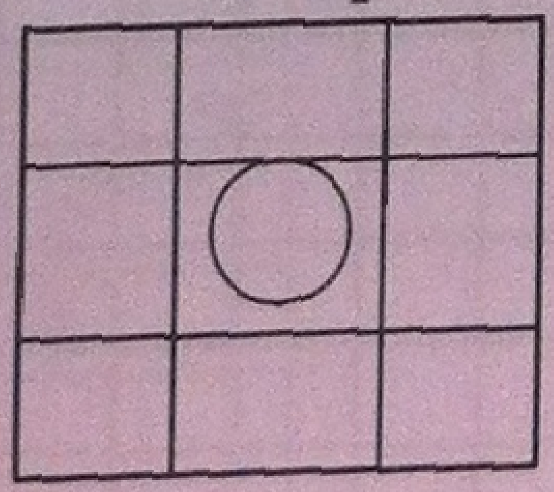
4. Als Reduktionsfunktion soll das Minimum des 3×3 Reduktionsfensters dienen.

5. Verteile die Grauwerte der Histogramme H_0, H_1 so auf die Ebenen der Minimumpyramide, dass
   - das Minimum jedes 3×3 Reduktionsfensters genau dem Elternpixel entspricht;
   - die Summe der Werte des 2×2 Roberts Kantendetektors minimal wird. In der Grundebene sind das 36 Werte und in Min_1 4 Werte, deren Summe durch Verteilen der Grauwerte von $H_0(g)$ und $H_1(g)$ so klein wie möglich werden sollen.

Min_0

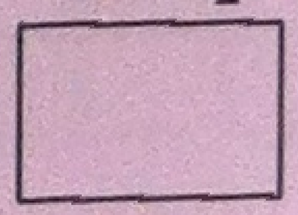


Min_1



$\sum(\text{Roberts}(Min_1)) =$ ______

Min_2



$\sum(\text{Roberts}(Min_0)) =$ ______

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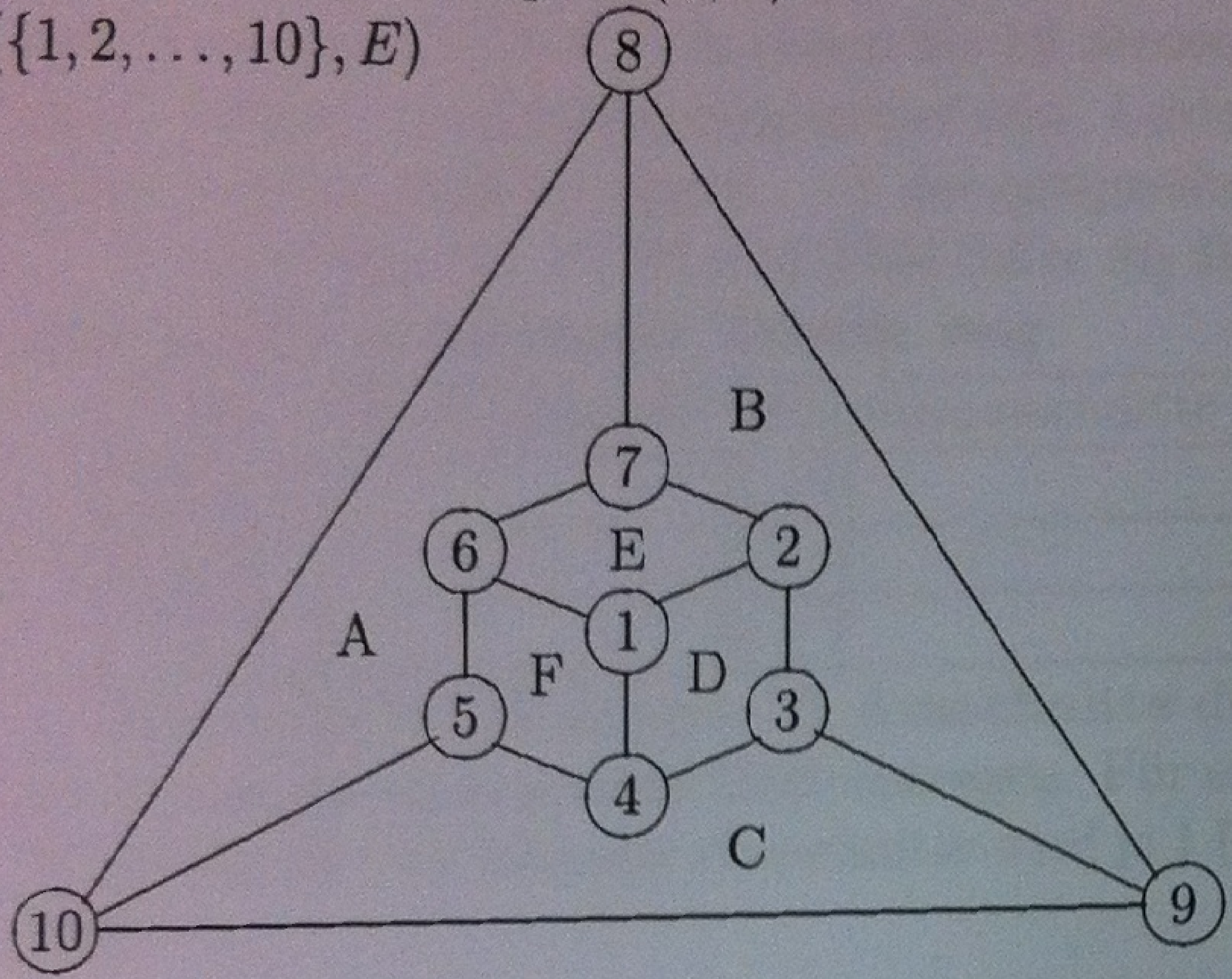
4 Dualer Graph und Kantenkontraktion (5)

Gegeben ist der Graph $G(V, S)$ mit 10 Knoten V und 15 Kanten S:

$G(\{1, 2, \ldots, 10\}, E)$



H	A	B	C	D	E	F
A						
B						
C						
D						
E						
F						

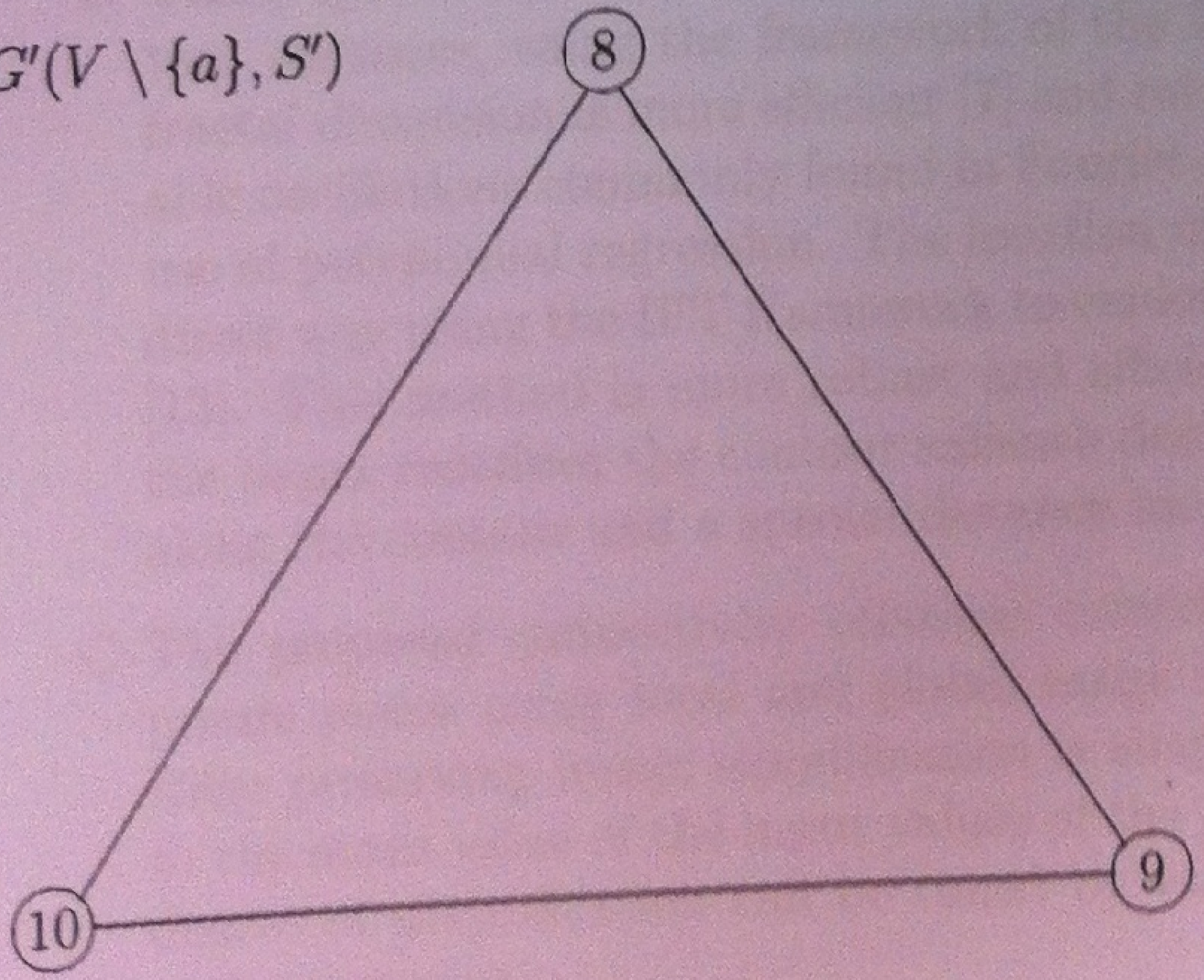
1. Bestimmen Sie die (obige) Adjazenzmatrix des dualen Graphen $H(R, S')$, mit Regionen $R = \{A, B, C, D, E, F\}$, und dualen Kanten $|S'| = |S| - 3$ ohne die Aussenfläche.

2. Kontrahieren Sie die Kante $(a, b) \in S$, wobei $a = \max M + 1$ (M ist die Menge der Ziffern Ihrer Matrikelnummer) und b der Nachbarknoten von a in G mit kleinstem Index ist: $(a, b) =$ .... Der Knoten a bleibt erhalten. Zeichne den Graphen $G' = G/(a, b)$ in den Teilgraphen G' am Ende ein.

3. Zeichne auch die Regionen R des dualen Graphen H' ein.

4. Bestimme die Adjazenzmatrix des dualen Graphen $H'(R, S'')$ wieder ohne die Aussenfläche.

$G'(V \setminus \{a\}, S')$



H'	A	B	C	D	E	F
A						
B						
C						
D						
E						
F						

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Teil III: Selektion von Literatur (16)

In Abschnitt 6 finden Sie 10 Titel wissenschaftlicher Publikationen. In Abschnitt 5 finden Sie 20 Literaturausschnitte (A-T) von denen Sie **12 diesen Titeln zuordnen müssen**. Einem Titel können somit mehrere Ausschnitte zugeordnet sein. Leider sind die Reihenfolge und die Zuordnungen, sowie einige Worte (markiert durch ...) der entsprechenden Beiträge verloren gegangen.

Je nach Wert der VORLETZTEN Ziffer M_6 Ihrer Matrikelnummer **streichen Sie 8 Literaturausschnitte in folgender Tabelle weg**:

M_6	Zu streichende Literaturausschnitte
0,1,2,3	A - H
4,5,6	G - N
7,8,9	M - T

Stellen Sie für die übrigen **12 Ausschnitte** die inhaltlichen Zuordnungen wieder her, indem Sie sie zu dem dazugehörenden Titel eintragen. Für eine korrekte Korrespondenz erhalten Sie 2 Punkte, für falsche und für fehlende Ausschnitte wird je 1 Punkt abgezogen. Maximal werden 16 Punkte gewertet.

5 Abstracts und Literaturausschnitte

A ... are not invariant to scale and translation, therefore the symbols are first scaled and translation normalized such that they are of the same dimension and their centroids are positioned at the origin. Each symbol is scaled to form a 100x100 pixel model for recognition so that non-uniform scaling in shapes will not affect the recognition outcome (i.e. a long, thin rectangle and a short, fat rectangle will both be recognized as rectangles). The original aspect ratio is preserved in the symbol beautification process and the specific geometric properties in a symbol can be computed from its structural decomposition.

B This paper has presented two effective shape descriptors, multiscale fractal dimension and contour saliences, using the framework of the IFT. The presented method to compute multiscale fractal dimension is more efficient [7] and robust than the one published in [2], since the undesirable oscillations commonly found in Fourier-based approaches have been eliminated here by the use of polynomial regression. The location of salience points along a contour was computed in a direct way using the IFT framework to exploit the relation between the contour and its skeletons [13]. This method is more robust and efficient than the approach presented in [2]. Moreover, the paper redefines the contour salience descriptor to include point location and salience value along the contour and a special distance metric.

C The proposed connectivity relations provide us with a tool for decomposing an image into puzzle pieces using local and global range constraints, as well as a connectedness constraint. Edge preserving image simplification is simply achieved by setting each connected component to the mean value of the input values of the pixels belonging to this connected component. The degree of simplification can be tuned by varying the values of the parameter associated with each constraint.

D This paper deals with effective separation of ... images suffering from various types of degradations including scanning noise, aging effects, uneven background, or foreground, etc. The proposed algorithm shows an excellent adaptability to tackle with these problems of uneven illumination and local changes or nonuniformity in background and foreground colors. The approach is primarily designed for (not restricted to) processing of color documents but it works well in the gray scale domain too...

E The majority of the existing methods for computing the orientation are area based i.e. the computation takes into account all points that belong to the shape not only the boundary points. Among those area based methods, the most standard one says that shape orientation is determined by its axis of the least second moment of inertia [13]. The axis of the least second moment of a shape is defined as a line that minimises the integral of the squared distances of the shape points to the line. When working with shapes represented by a set of discrete points (set of pixels, for example) then the integral should be replaced with the sum. Obviously, the method is motivated very naturally. Also, because it is area based, the standard method is very robust with respect to noise and boundary defects. Moreover, it is simple to compute in both real and discrete versionseven the closed formulas for the computation of the orientation could be derived in both versions.

F To achieve these objectives, a novel minimization criterion is proposed. It consists of the minimization of the error between the descending slope of the histogram and its piecewise linear regression. It belongs to the histogram-based algorithms, but, unlike the main available methods, its computation relies on a wide portion of the histogram rather than a single bin or a few local bins. The technique is presented for gradient images, but can be generalized to other types of images. It does not rely on a specific graylevel unimodal distribution, but on the hypothesis of a less populated class belonging to the tail of the histogram.

G ... The method exploits the information conveyed by the evolution of the training samples weights similarly to the Adaboost algorithm. Features are selected on the basis of their individual merit using a simple error function. The weights dynamics and its effect on the error function are utilised to identify and remove redundant and irrelevant features. In experiments we show that the performance of commonly employed learning algorithms using features selected by the proposed method is the same or better than that obtained with features selected by the traditional state-of-theart techniques

H Let $X \subset \mathbf{R}^n$ be an n dimensional observation space and $Y = -1, +1$ the set of labels. Consider a labelled training set of samples $S = x_i, y_i$, where $y_i \in Y$ denotes the label of sample $x_i \in X$ and $i = 1, 2, \ldots, m$ enumerates the elements of the set. The components of a particular sample vector, x_i, are denoted as $x_{i,j}$, where $j = 1, \ldots, n$, and we refer to them as features. Different features contribute diverse discriminatory power for the classification task. Some may be redundant, and therefore do not provide new information, or irrelevant, hence offer no information at all. The occurrence of these features can degrade the performance of a classifier.

I In fact, due to the variety of shapes as well as the diversity of applications there is probably no single method for computing shape orientation that could be efficiently and successfully applicable to all shapes. For that reason, several methods have been developed [410]. Different techniques have been used, including those based on geometric moments, complex moments, and principal component analysis, for example. The suitability of those methods strongly depends on the particular situation to which they are applied, as they each have their relative strengths and weaknesses.

J We expect, with perennial optimism, that in the years ahead vastly enlarged classification contexts, and judicious application of close-coupled human intervention, will lead to significant expansion in the application of visual pattern recognition systems. These techniques are synergistic: each improves the benefit from the other. My talk will highlight relevant examples drawn from OCR, forms processing, botany, physiognomy, and dermatology.

K How can we take advantage of the differences between human and machine cognitive abilities? Humans apply to recognition a rich set of contextual constraints and superior noise filtering abilities to excel in gestalt tasks, like object-background separation. Humans are also good at judging whether two images represent the same class. But computers can store thousands of images and associations between them, never forget a name or a label, and compute geometric moments and conditional probabilities. These differences suggest that a system that combines human and machine abilities can, in some situations, outperform both.

L For a signal not necessarily in multiresolution spaces, the ... may not be true. Aliasing error in the ... for a general signal was estimated, which can be computed from a given signal and a given scaling function. An application of the ... or cardinal scaling function was discussed in the last part of this paper, which is the computation of WST coefficients of signals. From the numerical results, the error of the computation of the WST coefficients of a signal by using the Mallat algorithm with the cardinal scaling function C_I we found is much smaller than the ones with the Haar scaling function, Daubechies D_4 and D_8.

M This paper presents two shape descriptors, multiscale fractal dimension and contour saliences, using a graph-based approach: the image foresting transform. It introduces a robust approach to locate contour saliences from the relation between contour and skeleton. The contour salience descriptor consists of a vector, with salience location and value along the contour, and a matching algorithm. We compare both descriptors with fractal dimension, Fourier descriptors, moment invariants, Curvature Scale Space and Beam Angle Statistics regarding to their invariance to object characteristics that belong to a same class (compact-ability) and to their ability to separate objects of distinct classes (separability).

N A recent category of shape-matching techniques, which does not need an approximate initial position, finds the optimal grid location for all vertices of a polygonal model by dynamic programming [14,15]. However, the method is quadratic in the number of potential locations, so the object needs to cover a large part of the image, otherwise localisation becomes prohibitively expensive (quantising the location to 1times in the order of one hour to detect a single object in an image). A powerful shape-matching method has been presented in Ref. [16], which uses integer quadratic programming to match sets of points sampled from object edges. In practice, either a good initial position or relatively clean images are required, similar to deformable template matching methods, because computational demands limit the amount of outliers the method can deal with.

O To design a generic document image binarization that works in both gray and color domain and can still handle a variety of degradation in documents including historical ones (pages from old printed books, handwritten manuscripts, microfilm images, etc.), we propose a new method that initially uses a connected component labeling approach to capture the spatially connected similar color pixels. This helps to rapidly locate zones containing information of interest. Next, dominant background components are determined looking at their size (in terms of member pixels) and then the entire image is divided into number of rectangular blocks (essentially not disjoint and are of different sizes) one around each dominant background components. These blocks represent local uniformity of illumination, background, etc. and respective foreground parts are treated against these local uniformities.

P Formally, a segmentation of the definition domain of an image can be defined as its partition into disjoint connected subsets (called segments) such that there exists a logical predicate returning true on each segment but false on any union of adjacent segments [1], [2], [3]. Connectivity relations are equivalence relations that naturally lead to partitions satisfying all conditions of a segmentation (the underlying logical predicate returning true if the segment is connected, false otherwise). For example, the trivial connectivity relation induced by the equality of gray-level partitions gray-scale images into segments corresponding to maximal connected components of uniform gray level [4]. They are called plateaus in fuzzy digital topology [5] and flat zones in mathematical morphology [6], [7], [8].

Q ... Detection by shape has been investigated in earlier work. The basic idea common to all methods is to define a distance measure between shapes, and then try to find minima of this distance. A classical method is chamfer matching [69], in which the distance is defined as the average distance from points on the template shape to the nearest point on the image shape. However, it has been repeatedly noted that chamfer matching does not cope well with clutter and shape deformations, e.g. Ref. [10]. Even if a hierarchy of many templates is used to cover deformations, the rate of false positives is rather high (typically > 1 false positive per image, FPPI).

R Our method assumes that: (i) a dominant pixel population produces the main peak of the histogram, that is the noise on the homogeneous regions in a gradient magnitude image; (ii) a secondary population contributes mainly to the tail of the histogram, i.e. the edges. The ... T, desired to select a maximum of edges while ensuring a minimum of false detection, is presumed to be located somewhere after the position of the maximum of the histogram and before the elongated part of the tail. The descending slope can be decomposed into two parts: a steeply descending slope immediately after the peak and a slightly descending slope in the flat tail (Fig. 3A). We propose to determine the two lines that best describe these two descending slopes. The point of abscissa that minimizes the error between the descending slope and the two lines, called the T-point, is chosen as the threshold. This method is referred to as the T-point algorithm, corresponding to the point where the line representation switches from the steep to the slight slope line.

S In this paper, we present an on-line recognition method for hand-sketched symbols. The method is independent of stroke-order, -number, and -direction, as well as invariant to scaling, translation, rotation and reflection of symbols. ... descriptors are used to represent symbols and three different classification techniques are compared: Support Vector Machines (SVM), Minimum Mean Distance (MMD), and Nearest Neighbor (NN).

T The classical ... has resulted in many applications and generalizations. From a multiresolution point of view, it provides the sinc scaling function. In this case, for a band-limited signal, its ... coefficients below a certain resolution level can be exactly obtained from the samples with a sampling rate higher than the Nyquist rate. In this research, we study the properties of cardinal orthogonal scaling functions (COSF), which provide the standard ... in multiresolution spaces with scaling functions as interpolants.

6 Welche Ausschnitte gehören zu folgenden Titel ?

0 A graph-based approach for multiscale shape analysis

Ausschnitt(e): B, M

Begründung(en):

1 On Sampling Theorem, Wavelets, and Wavelet Transforms

Ausschnitt(e): L, T

Begründung(en):

2 Boundary based shape orientation

Ausschnitt(e): E, I

Begründung(en):

3 Constrained Connectivity for Hierarchical Image Partitioning and Simplification

Ausschnitt(e): C, P

Begründung(en):

4 Object detection by global contour shape

Ausschnitt(e): N, Q

Begründung(en):

5 Feature selection based on the training set manipulation

Ausschnitt(e): G, H

Begründung(en):

6 Sketched Symbol Recognition using Zernike Moments

Ausschnitt(e): A, S

Begründung(en):

7 On foreground background separation in low quality document images

Ausschnitt(e): D, O

Begründung(en):

8 Robust threshold estimation for images with unimodal histograms

Ausschnitt(e): F, R

Begründung(en):

9 Visual Pattern Recognition in the Years Ahead

Ausschnitt(e): J, K

Begründung(en):