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

Schriftliche Prüfung aus Grundlagen der Digitalen Bildverarbeitung WS 2005/2006

Walter G. Kropatsch

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

Grundlagen der Digitalen Bildverarbeitung LV 183.126		Datum: 17.10.2006
Mat.Nr.	Name	Studium

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

Matlab Referenz

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).

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 = and(A,B)`
is a matrix whose elements are 1's where both A and B have non-zero elements, and 0's where either has a zero element.

`D = bwdist(BW)`
computes the Euclidean distance transform of the binary image BW. For each pixel in BW, the distance transform assigns a number that is the **distance between that pixel and the nearest nonzero pixel** of BW. bwdist uses the Euclidean distance metric by default. D is the same size as BW.

`BW2 = bwmorph(BW,'skel',n)`
with n = Inf, removes pixels on the boundaries of objects but does not allow objects to break apart. The pixels remaining make up the image skeleton. This option preserves the Euler number.

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

`J = imnoise(I,'gaussian',m,v)`
adds Gaussian white noise of mean m and variance v to the image I.

`J = imnoise(I,'salt & pepper',d)`
adds salt and pepper noise to the image I, where d is the noise density.

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

`~A`
equals not(A);

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 von 7 dieser 10 Bildoperationen. Tragen Sie bitte die Bildnamen (`A-X`) in die Kästchen □ der jeweiligen Operation ein. Jede korrekte Antwort wird mit zwei Punkten belohnt, für eine falsche Antwort wird ein Punkt von der Gesamtsumme abgezogen. Von den DezimalziffernIhrer Matrikelnummer wählen Sie die kleinste (MIN) und die größte Ziffer (MAX) und den Median (MED) aus:
$MIN = \square$, $MAX = \square$, $MED = \square$.
Diese 3 Fragen müssen Sie NICHT beantworten! Für entsprechend gute und korrekte Begründungen kann es Zusatzpunkte geben, die Verluste in anderen Abschnitten ausgleichen können!

Grundlagen der Digitalen Bildverarbeitung LV 183.126		Datum: 17.10.2006
Mat.Nr.	Name	Studium

0. `☐ = "Hough-Transform"( ☐ );`

   Begründung: ....

1. `☐ = bwdist( ☐ );`

   Begründung: ....

2. `☐ = bwdist( ~☐ );`

   Begründung: ....

3. `☐ = imnoise( ☐ ,'gaussian',0,0.2);`

   Begründung: ....

4. `☐ = imnoise( ☐ ,'salt & pepper',0.2);`

   Begründung: ....

5. `☐ = medfilt2( ☐ );`

   Begründung: ....

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

   Begründung: ....

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

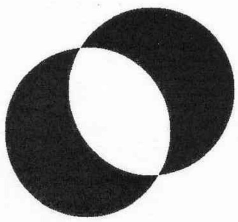
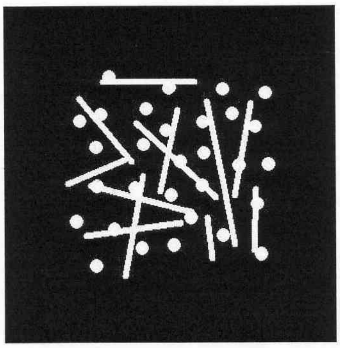
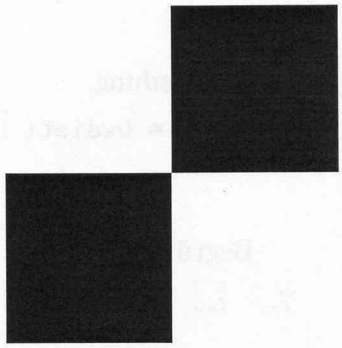
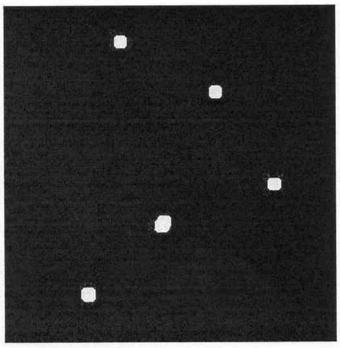
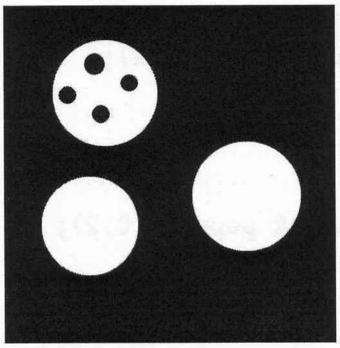
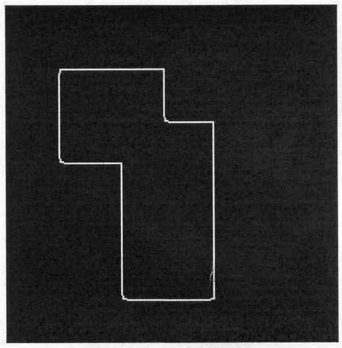
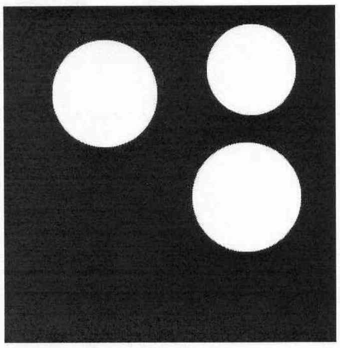
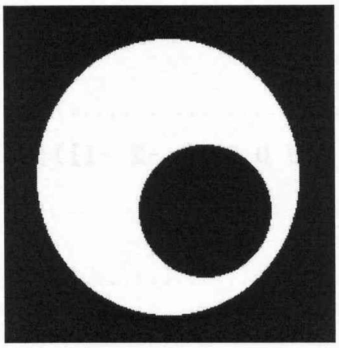
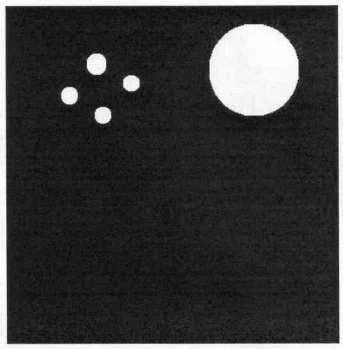
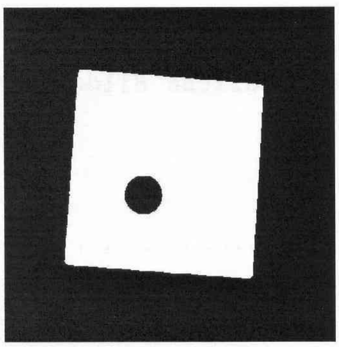
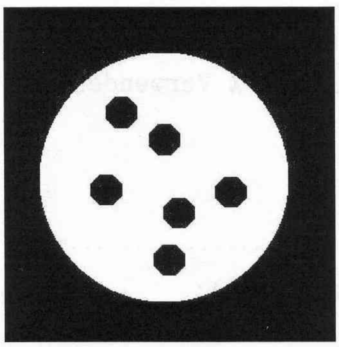
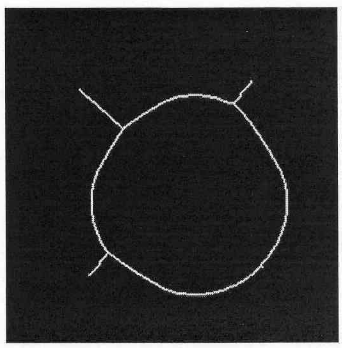
   Begründung: ....

8. `☐ = and( ☐ , not( ☐ )); % Verwenden Sie 3 unterschiedliche Bilder!`

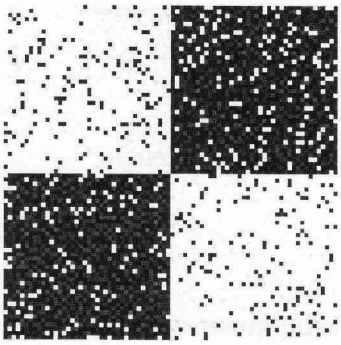
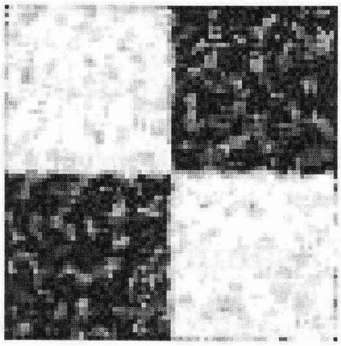
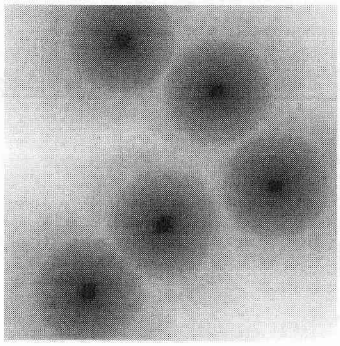
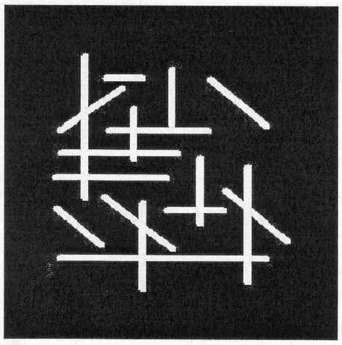
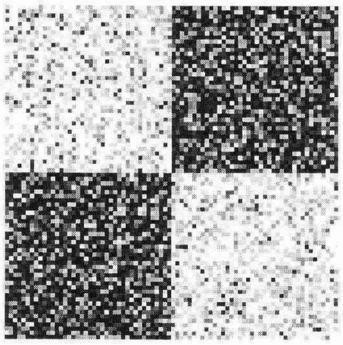
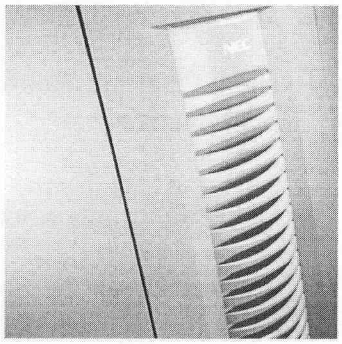
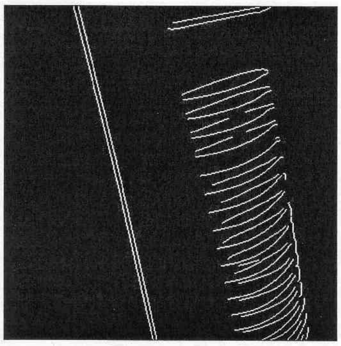
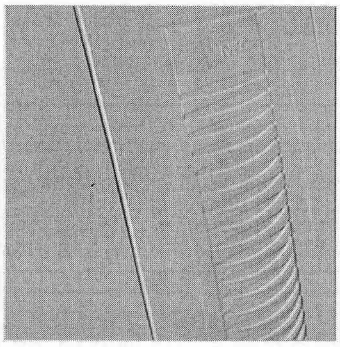
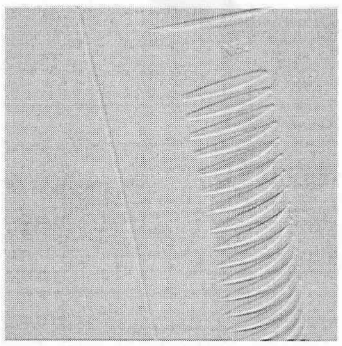
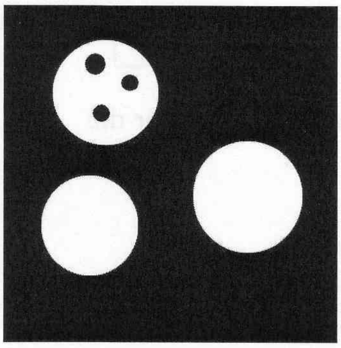
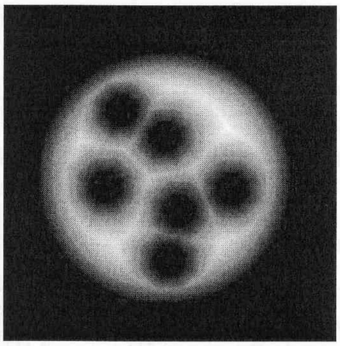
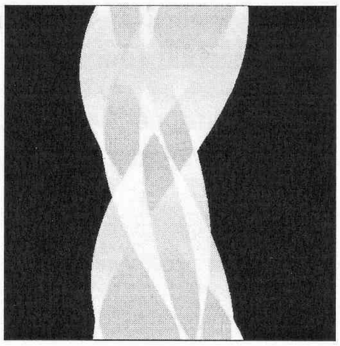
   Begründung: ....

9. `☐ = bwmorph( ☐ ,'skel',Inf);`

   Begründung: ....

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

Grundlagen der Digitalen Bildverarbeitung LV 183.126		Datum: 17.10.2006
Mat.Nr.	Name	Studium

Binärbilder	Grauwertbilder	
M= 	N= 	O= 
P= 	Q= 	R= 
S= 	T= 	U= 
V= 	W= 	X= 

Grundlagen der Digitalen Bildverarbeitung LV 183.126		Datum: 17.10.2006
Mat.Nr.	Name	Studium

Teil II: Mathematisches Nachvollziehen (20)

In diesem Teil sollen Sie einfache Bildverarbeitungsoperationen numerisch nachvollziehen.

1 Morphologie und Zusammenhang (5)

Füllen Sie in die Kästchen der folgenden Matrix die Ziffern Ihrer Matrikelnummer ein:

y	1	2	3	4	5	6	7
x							

1. Die 7 Pixel mit Koordinaten (x, y) kennzeichnen Sie bitte in der unten stehende Bildmatrix mit $\bullet$.

2. Diese Binärmatrix schließen Sie mit folgendem Strukturelement: $\begin{array}{|c|c|} \hline x & x \\ \hline x & \bullet \\ \hline x & x \\ \hline \end{array}$ ab (CLOSE) und markieren die neuen 1-Pixel mit einem x. Jedes Element der Matrix hat danach eines der Zeichen $\square$, $x, \bullet$ Für den Bildrand verwenden Sie bitte den zyklischen Abschluss.

$y \uparrow$										
7										
6										
5										
4										
3										
2										
1										
	0	1	2	3	4	5	6	7	8	9 $\rightarrow x$

$y \uparrow$										
7										
6										
5										
4										
3										
2										
1										
	0	1	2	3	4	5	6	7	8	9 $\rightarrow x$

3. Wieviele 8-Zusammenhangskomponenten (OHNE zyklischen Abschluss) hat das abgeschlossene Binärbild (nur x und $\bullet$)? $CC_8 = \square$.

4. Bestimmen Sie die Co-Occurence Matrix der 3 auftretenden Symbole $\square$, $\bullet, x$ für die Verschiebung $\delta = (0, 2)$ (wieder bei zyklischem Abschluss, $|N_\delta| = 70!$):

$P_\delta =$

	$\square$	$\bullet$	x	Σ
$\square$	/70	/70	/70	/70
$\bullet$	/70	/70	/70	/70
x	/70	/70	/70	/70
Σ	/70	/70	/70	/70

2 Integral Image und predictive Coding (5)

1. Füllen Sie die Ziffern Ihrer Matrikelnummer $M_1, M_2, \ldots M_7$ in die folgende Tabelle und berechnen dann die Werte von S_i nach folgender Formel: $S_1 = M_1; S_{i+1} = S_i + M_{i+1} + i$ für $i = 1, 2, 3, 4, 5, 6$.

i	1	2	3	4	5	6	7
M_i							
S_i							
Spalte $x_i = \lfloor S_i/10 \rfloor$							
Zeile $y_i = \mathrm{mod}(S_i, 10)$							

2. Daraus ergeben sich dann die Koordinaten jener Pixel (x_i, y_i), die Sie in folgender Matrix B mit 1 markieren. Die restlichen Pixel sind 0 und können leer gelassen werden.

3. Füllen Sie dann in die Kästchen $I(B)$ die Werte des Intergral Images des Binärbildes B.

$B =$

	0	1	2	3	4	5	6	7	8	9
0										
1										
2										
3										
4										
5										
6										
7										
8										
9										

$I(B) =$

	0	1	2	3	4	5	6	7	8	9
0										
1										
2										
3										
4										
5										
6										
7										
8										
9										

4. Das Integral Image I soll mit einem linearen Prädiktor der Ordnung 3 mit folgenden Koeffizienten

$a_1 = -1$	$a_2 = +1$
$a_3 = +1$	$\tilde{B}(i,j)$

übertragen werden (Array $\tilde{B}$ dient der Hilfestellung und muß nicht ausgefüllt werden!). Die Differenz $D(i,j) = I(i,j) - \tilde{B}(i,j)$ wird dann mit Lauflängenkodierung (Run lenght code) zeilenweise übertragen. Geben Sie den Code jeder Zeile an:

$\tilde{B} =$

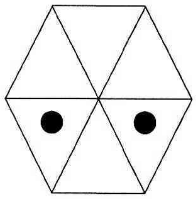
	0	1	2	3	4	5	6	7	8	9
0										
1										
2										
3										
4										
5										
6										
7										
8										
9										

Zeile 0 : ....
Zeile 1 : ....
Zeile 2 : ....
Zeile 3 : ....
Zeile 4 : ....
Zeile 5 : ....
Zeile 6 : ....
Zeile 7 : ....
Zeile 8 : ....
Zeile 9 : ....

Grundlagen der Digitalen Bildverarbeitung LV 183.126		Datum: 17.10.2006
Mat.Nr.	Name	Studium

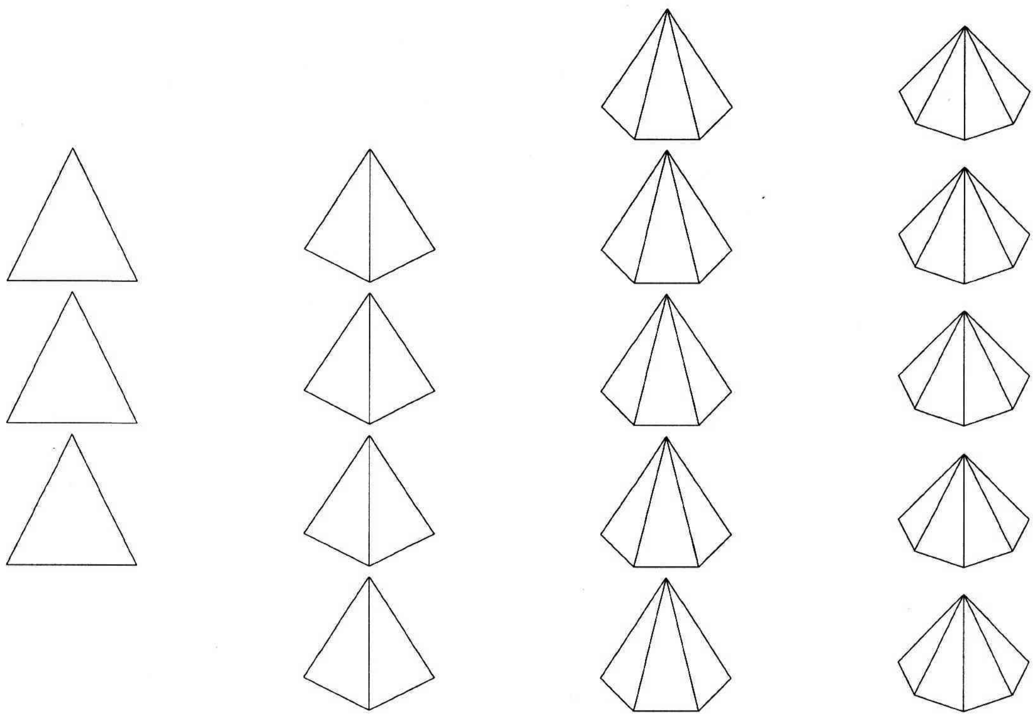
3 Aspect Graph einer Pyramide (5 P)

1. Gegeben sei eine regelmäßige Pyramide mit 6 Seiten, die Sie von allen Seiten betrachten. Sie können die Pyramide weder von unten noch von oben sehen. Zwei der Seiten sind mit einem Punkt (•) markiert:



2. Ergänzen Sie die folgenden Ansichten des Aspectgraphen
   (a) durch Kennzeichnung der markierten Fläche (•),
   (b) durch Wegstreichen von unmöglichen Ansichten und
   (c) durch Einfügen der Kanten des Aspectgraphen.

   Achtung: alle Ansichten des Aspect-Graphen müssen verschieden sein!



Der Graph hat ☐ Knoten und ☐ Kanten.

Grundlagen der Digitalen Bildverarbeitung LV 183.126		Datum: 17.10.2006
Mat.Nr.	Name	Studium

4 Pyramide (5 P)

1. Tragen Sie in die durch ○ gekennzeichneten Felder der Pyramide P spaltenweise die Ziffern Ihrer Matrikelnummer ein.

2. Ergänzen Sie die restlichen Felder der $2 \times 2/4$ Mittelwertpyramide und der Reduce-Expand-Laplace-Pyramide mit ganzen Zahlen so, dass für alle Elemente von P die Reduktionsfunktion erfüllt ist und in L betragsmässig möglichst kleine Werte stehen. Als Expand-Funktion verwenden Sie dabei eine einfache Projektion .

$P =$

M_1	M_2	M_3	M_4
○			
	○		
		○	
			○

M_5	M_6

M_7
○

$L = E(P) - P =$

○	
	○

Begründung: ....

....

....

....

....

....

....

Grundlagen der Digitalen Bildverarbeitung LV 183.126		Datum: 17.10.2006
Mat.Nr.	Name	Studium

Teil III: Selektion von Literatur (16)

Die folgenden Literaturausschnitte stammen aus neueren Artikeln einiger Zeitschriften und Konferenzen.

In der Beilage finden Sie eine Liste mit je 10 numerierten Titeln und eine mit 20 Abstracts. Leider ist die Reihenfolge und die Zuordnungen, sowie einige Worte der entsprechenden Beiträge verloren gegangen.

5 Abstracts und Literaturausschnitte

A More and more images have been generated in digital form around the world. There is a growing interest in finding images in large collections or from remote databases. In order to find an image, the image has to be described or represented by certain features. Shape is an important visual feature of an image. Searching for images using shape features has attracted much attention. There are many shape representation and description techniques in the literature. In this paper, we classify and review these important techniques. We examine implementation procedures for each technique and discuss its advantages and disadvantages. Some recent research results are also included and discussed in this paper. Finally, we identify some promising techniques for image retrieval according to standard principles.

B Improving the accuracy of line segment detection reduces the complexity of subsequent high-level processing common in cartographic feature detection. We developed a new extension to the Hough transform and reported on its application to building extraction. We expanded the Hough space by a third parameter, the horizontal or vertical coordinate of the image space, to provide incremental information as to the length of the lineal feature being sought. Using this extended HT transform allowed us to more accurately detect the true length of a line segment. In addition, we used a Bayesian probabilistic approach to process our extended Hough space that further increased the accuracy of our extended Hough transform.

C The hierarchical segmentation algorithm ... produces from an image and a seed point P a set of hierarchically related regions of points which contain P. In other words, each region in the set contains all regions smaller than itself. The algorithm proceeds in two main stages. The first stage performs connected component analysis based on Saturation and Value channels in HSV space (Hue, Saturation, Value). Hue is ignored due to image properties of the scene camera. For every pixel in the image, the two-channel values are stored in a color map structure. The color map is then scanned to find ten representative colors. The representative colors are added incrementally and are chosen based on maximum distance from each previously found representative color. Each pixel is then set to its nearest representative color, based on its original color and proximity in SV space. Finally, connected component analysis is performed to group locally adjacent regions of the same color.

D Based on a novel lighting compensation technique and a nonlinear color transformation, our method detects skin regions over entire image. The algorithm constructs eye, mouth and boundary maps for verifying each candidate.

E Zhang and Lu have tested geometric moment invariants on a standard shape database used by MPEG-7 [57]. They have found that geometric moment invariants perform very well on similarity transformed and affinely transformed contour-based shapes. They even outperform grid descriptor for these simple shapes. However, they perform poorly for arbitrarily distorted contour-based shapes. For region-based shapes which have interior content, they only perform satisfactorily on rotated shapes; while for scaled shapes, perspectively transformed shapes and subjective test shapes, they perform poorly. The finding indicates that geometric moment invariants are suitable for describing simple shapes.

F Unfortunately, most vision problems, even those that were first tackled in the 1950's, are mathematically ill-defined (reading handwritten words, counting cells, recognizing buildings). Real-world visual domains do not satisfy simple mathematical (even probabilistic) models. Even if adequate scene models could be formulated, problems that involve inferring information about a scene from images are often mathematically ill-posed or computationally intractable; but the primary reason why vision is hard for computers is that the scene models used (often tacitly) in today's computer vision systems are unrealistic, and this situation is likely to persist for a long time to come.

G In most of the existing color image segmentation approaches, the definition of a region is based on similar color. Monochrome image segmentation techniques can be extended to color image, such as histogram thresholding, clustering, region growing, edge detection, fuzzy logic and neural networks, by using RGB or their transformations (linear/non-linear).
Generally speaking, monochrome image segmentation approaches are based on either discontinuity and/or homogeneity of gray level values in a region. The approach based on discontinuity tends to partition an image by detecting isolated points, lines and edges based on abrupt changes in gray levels. The approaches based on homogeneity include thresholding, clustering, region growing, and region splitting and merging, etc.

H The color of mouth region contains stronger red component and weaker blue component than other facial regions. Hence, the chrominance component C_r is greater than C_b in the mouth region. We further notice that the mouth has a relatively low response in the C_r/C_b feature, but it has a high response in C_r^2. We construct the mouth map as follows:

$$MouthMap = C_r^2 \cdot \left(C_r^2 - \eta \cdot C_r/C_b\right)^2, \tag{1}$$

$$\eta = 0.95 \cdot \frac{\frac{1}{n}\sum_{(x,y)\in\mathcal{FG}} C_r(x,y)^2}{\frac{1}{n}\sum_{(x,y)\in\mathcal{FG}} C_r(x,y)/C_b(x,y)}, \tag{2}$$

where both C_r^2 and C_r/C_b are normalized to the range $[0, 255]$, and n is the number of pixels within the face mask, $\mathcal{FG}$. The parameter η is estimated as a ratio of the average C_r^2 to the average C_r/C_b.

I The second stage of the algorithm performs graph contraction of the previously found connected components. Each component is treated as a node in a graph, with edges connecting adjacent regions in the graph. For a specified number of iterations, locally adjacent nodes are grouped based on distance in SV color space. Grouped nodes are then contracted to form one node while preserving the adjacency structure of the graph. This iterative approach allows for multiple "levels" of segmentation and accounts for the hierarchical nature of the results: each iteration of graph contraction potentially grows the region containing P. If we consider the seed point P to represent the current focus of a user's gaze, we can interpret the set of regions produced by the algorithm as hypotheses regarding the spatial extent of likely objects containing P. For example, if the user's point of regard were resting on a coffee cup atop a table, segmentation level 2 might be the region of points comprising the cup, and segmentation level 4, produced by two further iterations of graph contraction, might be the region of points comprising the tabletop.

J We detected short line segments with both approaches and compared their results using a gain curve derived from the ROCs[1]. A gain curve is obtained from all ROC curves with the similar statistics; only the mean value of line pixels is changed to vary the difficulty of detection. To generate a ROC curve, 10,000 random images were generated. Background pixels of typical Hough transformed images are generally exponentially distributed with location parameter μ_0, and scale parameter λ, which was written as $H_0 : E(\mu_0, \lambda)$. In addition, we considered a Gaussian distribution for line segment pixels as $H_1 : G(x, 30)$, where x is the mean, and was varied to generate statistics for the gain curve. To construct the gain curve, we chose a specific difference between the two means of H_0 and H_1, and then determined the percentage gain .... We considered line segments of lengths, 1%, 3%, 5%, and 10% of the maximum possible length in 256 256 pixel images with 256 gray levels. Because many interesting man-made objects such as building sides in overhead imagery consist solely of short line segments (1% and 3%), the measurement of rather short line segments are chosen as comparable long line segments (5% and 10%), to compare the most useful response.

K In this paper, we propose a new method to characterise a curve by means of the hierarchical computation of a multiresolution structure. This structure, consisting of successive lower resolution versions of the same object, is processed using the linked pyramid approach. We adapt the multiresolution pixel linking algorithm to the processing of curve contours which are described by their chain-code. We also introduce a selective class selection process which allows application of the algorithm to segmentation and detection of contour features. The resulting framework presents good performance for a wide range of object sizes without the need of any parameter tweaking, and allows detection of shape detail at different scales.

L The last appearance (moving from the bottom to the top) of a corner in the pyramid gives information about the scope of the curvature; we therefore call it the *measure of scope (S)*. The first appearance reflects the size of curvature; it is called the *measure of curvature-approximation (C)*. The sharper the enclosed angle, the earlier the curvature point will be detected. The number of levels at which a corner is detected is called the *measure of importance (I)*. For individual corners, it was proved that they must be detected when they satisfy the corner conditions. The measure of importance describes the possibility of the appearance of a corner in the pyramid. It is introduced to make the description usable for more corners. The three measurements stabilize the description in the sense that small changes in the input result in small changes in the description.

M Suppose the input gray image with size $N \times N$ has been compressed into the compressed image via quadtree and shading representation. Assume that the number of blocks in the representation is B, commonly $B < N^2$ due to the compression effect. This paper first derives some closed forms for computing the mean/variance of any block and for calculating the two statistical measures of any merged region in O(1) time. It then presents an efficient $O(B\alpha(B))$-time algorithm for performing region segmentation on the compressed image directly where $\alpha(B)$ is the inverse of the Ackerman's function and is a very slowly growing function. With the same time complexity, our results extend the pioneering results by Dillencourt and Samet from the map image to the gray image.

N The design of a pattern recognition system essentially involves the following three aspects: 1) data acquisition and preprocessing, 2) data representation, and 3) decision making. The problem domain dictates the choice of sensor(s), preprocessing technique, representation scheme, and the decision making model. It is generaly agreed that a well-defined and sufficiently constrained recognition problem (small intraclass variations and large interclass variations) will lead to a compact pattern representation and a simple decision making strategy. ...The four best known approaches for pattern recognition are: 1) template matching, 2) statistical classification, 3) syntactic or structural matching, and 4) neural networks.

O In this paper, a color image segmentation approach based on homogram thresholding and region merging is presented. The homogram considers both the occurrence of the gray levels and the neighboring homogeneity value among pixels. Therefore, it employs both the local and global information. Fuzzy entropy is utilized as a tool to perform homogram analysis for finding all major homogeneous regions at the first stage. Then region merging process is carried out based on color similarity among these regions to avoid oversegmentation. The proposed homogram-based approach (HOB) is compared with the histogram-based approach (HIB). The experimental results demonstrate that the HOB can find homogeneous regions more effectively than HIB does, and can solve the problem of discriminating shading in color images to some extent.

P Any *linear* property of an image is a weighted sum of its pixel values ([218], Ch. 7). *Moments* are an important class of linear properties in which the weights are monomials of the form $x^i y^j$ [127, 128, 85, 5]. An image can be normalized with respect to translation, rotation, and scale by shifting, rotating, and rescaling it so as to standardize the values of its first- and second-order moments ($1 \leq i + j \leq 2$). But many important image properties cannot be expressed as linear combinations of local properties [178].

Q Invariant pattern recognition is desirable in many applications, such as character and face recognition. Early research in statistical pattern recognition did emphasize extraction of invariant features which turns out to be a very difficult task. Recently, there has been some activity in designing invariant recognition methods which do not require invariant features. Examples are the nearest neighbor classificr using tangent distance [152] and deformable template matching [84]. These approaches only achieve invariance to small amounts of linear transformations and nonlinear deformations. Besides, they are computationally very intensive.

R The combination of these three components - stabilisation process, correction of crossed links and selective propagations - results in the transformation of the chain-code at the base in a stepwise constant function that characterises the contour and allows for a consistent and robust segmentation. The discontinuity points of the chain-code correspond to the extremes of the segments, whereas the value of the chain-code at the steps gives their orientation.

S Before presenting our proposed region-segmentation algorithm on the S-tree representation, we first present an efficient method for calculating the mean and the variance of a block in O(1) time. The calculated mean and the variance of one block will be used in the region-merging process.

T A multiresolution description of planar curves using corners and the curve pyramid bas been presented. Continuous curves under smoothing have been examined, and the results used to define measures that stabilize the description. A method has been developed for detecting corners of digital curves in parallel. This local method has been analyzed; it was found that corners are detected in all cases when the straight lines enclose an angle of at least $63.4^0(108.4^0)$ and the distance from one corner to the next is a receptive field (a receptive region of three cells).

6 Welche Ausschnitte gehören zu folgenden Titel

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0 Color image segmentation based on homogram thresholding and region merging

Ausschnitt(e): ....

Begründung(en): ....

1 From Image Analysis to Computer Vision: Motives, Methods, and Milestones, 1955-1979

Ausschnitt(e): ....

Begründung(en): ....

2 Review of shape representation and description techniques

Ausschnitt(e): ....

Begründung(en): ....

3 Statistical Pattern Recognition: A Review

Ausschnitt(e): ....

Begründung(en): ....

4 Efficient region segmentation on compressed gray images using quadtree and shading representation

Ausschnitt(e): ....

Begründung(en): ....

5 A Syntactic Approach to Scale-Space-Based Corner Description

Ausschnitt(e): ....

Begründung(en): ....

6 Corner detection and curve segmentation by multiresolution chain-code linking

Ausschnitt(e): ....

Begründung(en): ....

7 Extended Hough transform for linear feature detection

Ausschnitt(e): ....

Begründung(en): ....

8 Flycatcher: Fusion of Gaze with Hierarchical Image Segmentation for Robust Object Detection

Ausschnitt(e): ....

Begründung(en): ....

9 Face Detection in Color Images

Ausschnitt(e): ....

Begründung(en): ....