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

Schriftliche Prüfung aus Grundlagen der Digitalen Bildverarbeitung WS 2007/2008

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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. 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.

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

`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.

`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.

`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:

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

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

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

`SE = strel('disk',R)`
creates a flat, disk-shaped structuring element, where R specifies the radius.

`~A`
equals not(A);

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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 letzten 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, einen Abzugspunkt für eine falsche Antwort. Für entsprechend gute und korrekte Begründungen kann es Zusatzpunkte geben, die Verluste in anderen Abschnitten ausgleichen können!

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

Begründung: .....

1. ☐ = `conv2(` ☐ `,[1/9 1/9 1/9; 1/9 1/9 1/9; 1/9 1/9 1/9]);`

Begründung: .....

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

Begründung: .....

3. ☐ = `edge(` ☐ `,'canny',[0.4 0.5],1);`

Begründung: .....

4. ☐ = `im2bw(` ☐ `,110/255);`

Begründung: .....

5. ☐ = `im2bw(` ☐ `,200/255);`

Begründung: .....

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

Begründung: .....

7. ☐ = `bwdist(` ☐ `);`

Begründung: .....

8. ☐ = `bwdist(` ☐ `);`

Begründung: .....

9. ☐ = `"Hough-Transform"(W);`

Begründung: .....

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Binärbilder

A=

B=

C=

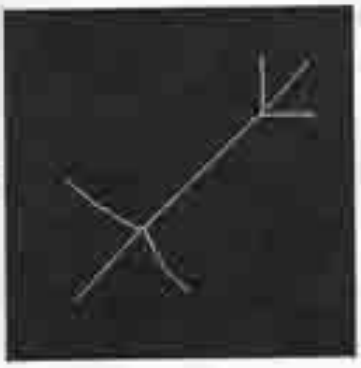
D=

E=

F=

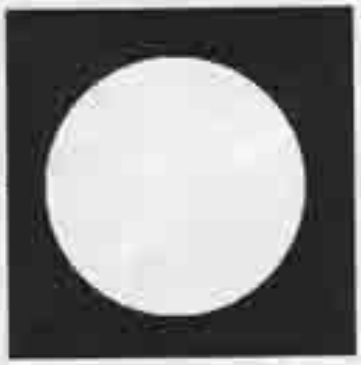
G=

H=

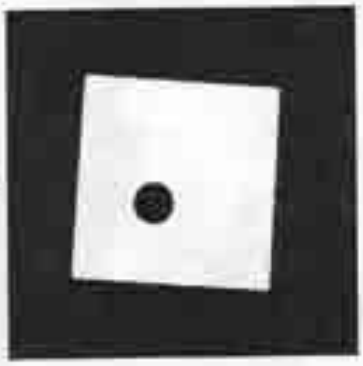


I=

J=



K=



L=

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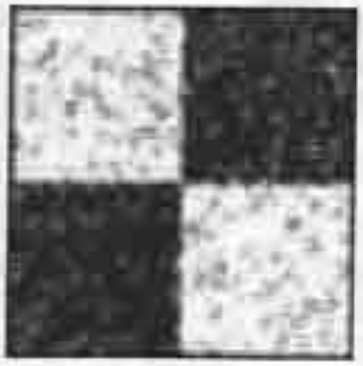
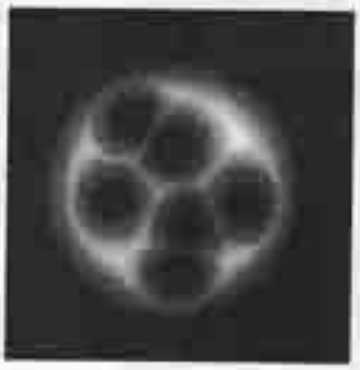
Grauwertbilder

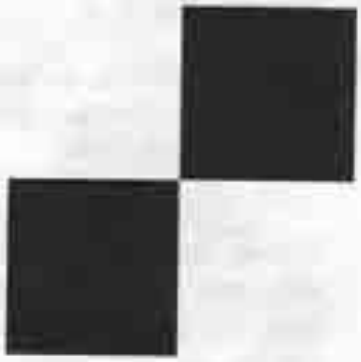
M= 

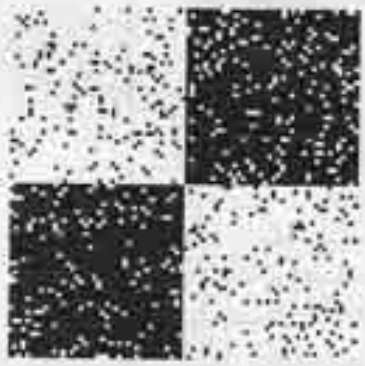
N= 

O= 

P= 

Q= 

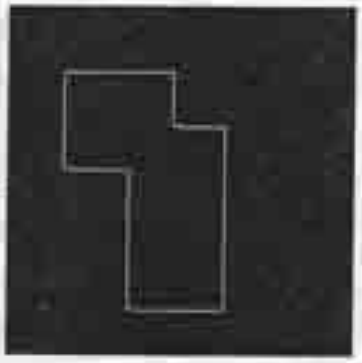
R= 

S= 

T= 

U= 

V= 

W= 

X= 

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Teil II: Mathematisches Nachvollziehen (20)

In diesem Teil sollen Sie einfache Bildverarbeitungsoperationen numerisch nachvollziehen.

1 Threshold und RAG-Kontraktion (5)

1. Das Grauwertbild B hat seine Grauwerte aus dem Bereich $[0, 9]$.

2. Markieren Sie in der folgenden Tabelle die Ziffern Ihrer Matrikelnummer durch Einkreisen der jeweiligen Ziffer.

0	1	2	3	4	5	6	7	8	9

   Daraus ergeben sich 2 bis 8 Grauwertintervalle mit 1 bis 9 aufeinanderfolgenden Ziffern, die markierten Werte kennzeichnen jeweils die untere Grenze des Intervalls. Beispiel:

   $\boxed{0, 1, 2, 3, 4 \ldots}$ erzeugt die Intervalle $[0, 2], [3, 3], [4, \ldots]$.

3. Zeichnen Sie die Grenzen zwischen den dadurch definierten Regionen im Bild B (als Crack-Codes) ein!

4. Der Region Adjacency Graph (RAG) besteht dann aus Knoten, die durch ein Intervall bestimmt werden. Dabei kann natürlich eine Ziffer mehrmals auftreten, wenn der Ziffer mehrere Zusammenhangskomponenten entsprechen. Zeichnen Sie den RAG des Bildes B!

5. Im RAG gibt es Kanten, deren Endpunkte den Ziffern Ihrer Matrikelnummer in der Reihenfolge ihres Auftretens entsprechen. Kontrahieren Sie all jene Kanten $(M_i, M_{i+1}), i = 1, 2, 3, 4, 5, 6$ und zeichnen den vereinfachten Graphen mit allen Self-Loops und Mehrfachkanten. Sollte ein Konten mehrere Kontraktionsmöglichkeiten haben, so wählen sie nur eine davon aus.

$$B = \begin{pmatrix} 2 & 2 & 5 & 5 & 5 & 3 & 3 \\ 2 & 0 & 0 & 5 & 9 & 9 & 3 \\ 8 & 0 & 0 & 6 & 9 & 9 & 8 \\ 8 & 0 & 0 & 6 & 9 & 9 & 8 \\ 1 & 0 & 0 & 7 & 9 & 9 & 4 \\ 1 & 1 & 7 & 7 & 7 & 4 & 4 \end{pmatrix}$$

RAG

Kontraktion

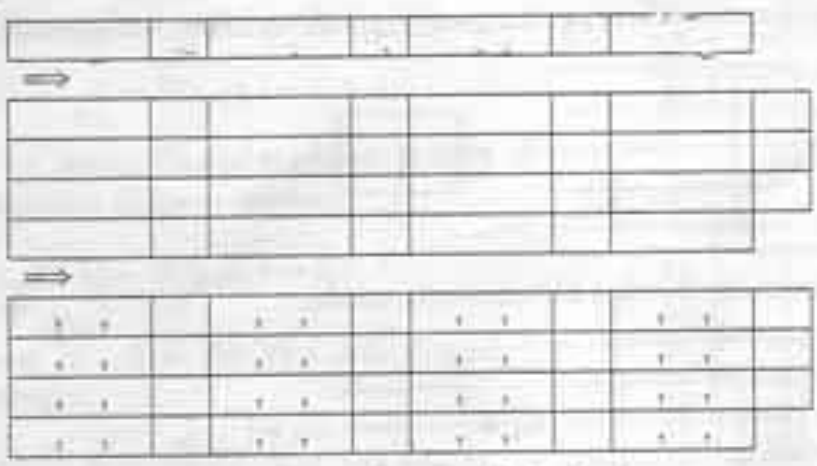
2 Hilbert Scan und Crack Code (5)

1. Der Hilbert Scan durchläuft alle Pixel eines quadratischen Bildes entlang einer einzigen Folge von 4-zusammenhängenden Pixeln. Diese Folge kann mit dem Crack-Code dargestellt werden.

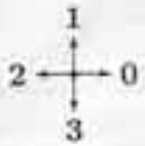
2. Folgende Grammatik $H = (\{0,1,2,3\}, \{S_0, S_1, S_2, S_3, T_0, T_1, T_2, T_3\}, S_i, P)$ erzeugt die Folge von Crack-Codes: P:

$S_0 \longrightarrow$	T_1	1	S_0	0	S_0	3	T_3	1	0	3
$S_1 \longrightarrow$	T_2	2	S_1	1	S_1	0	T_0	2	1	0
$S_2 \longrightarrow$	T_3	3	S_2	2	S_2	1	T_1	3	2	1
$S_3 \longrightarrow$	T_0	0	S_3	3	S_3	2	T_2	0	3	2
$T_0 \longrightarrow$	S_3	3	T_0	0	T_0	1	S_1	3	0	1
$T_1 \longrightarrow$	S_0	0	T_1	1	T_1	2	S_2	0	1	2
$T_2 \longrightarrow$	S_1	1	T_2	2	T_2	3	S_3	1	2	3
$T_3 \longrightarrow$	S_2	2	T_3	3	T_3	0	S_0	2	3	0

3. Als Startsymbol wählen Sie S_i mit i = die Häufigkeit der Ziffer 5 in Ihrer Matrikelnummer. Sollte 5 häufiger als 3 mal auftreten, so starten Sie mit S_3. Ersetzen Sie in der Entwicklung alle Nicht-Terminalsymbole bevor Sie einen neuen Entwicklungszyklus starten ("Parallelentwicklung"). Erzeugen Sie den Crack-Code für ein 8×8 grosses Bild: $S_i \Longrightarrow$



4. Zeichnen Sie im folgenden 8×8 Gitter den Crack-Code ein:



3 Laplacepyramide (5 P)

1. Eine kleine Laplacepyramide mit drei Ebenen L_0, L_1, L_2 ist gegeben durch:

$$L_0 = B \cdot \begin{pmatrix} 1 & 1 & ? & 0 \\ ? & 1 & 0 & 0 \\ -1 & 2 & -1 & ? \\ ? & 2 & 2 & -1 \end{pmatrix}, L_1 = B \cdot \begin{pmatrix} 1 & ? \\ 0 & 0 \end{pmatrix}, L_2 = A$$

   wobei die mit '?' gekennzeichneten Zellen so zu wählen sind, dass die rekonstruierte $2 \times 2/4$ Pyramide als Reduktionsfunktion den Mittelwert hat.

2. Die skalaren Faktoren A und B bestimmen Sie aus den Ziffern Ihrer Matrikelnummer wie folgt:

$$A = \text{Median}\{M_i | i = 1,2,3,4,5,6,7\} + \max\{M_i | i = 1,2,3,4,5,6,7\} = \boxed{}$$

$$B = \lfloor A/3 \rfloor = \boxed{}$$

3. Füllen Sie die sich ergebenden Werte der Laplacepyramide in folgende Matrizen ein:

$L_0 =$ | | | | |, $L_1 =$ | | |, $L_2 = \boxed{}$

4. Rekonstruieren Sie daraus die $2 \times 2/4$ Mittelwertpyramide:

$G_0 =$ | | | | |, $G_1 =$ | | |, $G_2 = \boxed{}$

Begründung: .....

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4 Predictive Coding (5)

1. Das Grauwertbild B berechnet sich aus den Ziffern $M_1, M_2, \ldots M_5$ Ihrer Matrikelnummer nach

   06277

   $$B(i,j) = \sum_{1 \le k \le 5, k \ne i, k \ne j} M_k; i,j = 1,2,\ldots,5$$

   Hinweis: nützen Sie die Symmetrie und Ziffernsumme zur Berechnung!

2. Das Bild B wird mit einem linearen Prädiktor der Ordnung 3 mit folgenden Koeffizienten

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

   übertragen, wobei $\tilde{B}(1,1) = B(1,1)$, die Elemente der ersten Zeile sich aus dem jeweilig linken Nachbar

   $$\tilde{B}(i+1,1) = B(i,1), i = 2,3,4$$

   und jene der ersten Spalte aus dem jeweilig darüber liegenden Element ergeben,

   $$\tilde{B}(1,j+1) = B(1,j), j = 2,3,4.$$

3. Die Differenz $D(i,j) = B(i,j) - \tilde{B}(i,j)$ wird dann übertragen.

4. Erklären Sie die spezielle Struktur von $D(i,j)$.

B:

	M_1	M_2	M_3	M_4	M_5
$M_1 =$					
$M_2 =$					
$M_3 =$					
$M_4 =$					
$M_5 =$					

$\tilde{B}$:

	M_1	M_2	M_3	M_4	M_5
M_1					
M_2					
M_3					
M_4					
M_5					

D:

	M_1	M_2	M_3	M_4	M_5
M_1					
M_2					
M_3					
M_4					
M_5					

Begründung: .....

.....

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.....

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Teil III: Selektion von Literatur (16)

In Abschnitt 6 finden Sie 10 Titel wissenschaftlicher Publikationen die kürzlich veröffentlicht wurden. In Abschnitt 5 finden Sie 20 Literaturausschnitte (A-T) von denen Sie **12 diesen Titeln zuordnen müssen**. Einem Titel können mehrere aber auch keine 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 Ihrer Matrikelnummer streichen Sie 8 Literaturausschnitte weg. Diese ergeben sich aus folgender Tabelle (m bezeichnet die vorletzte Ziffer Ihrer Matrikelnummer):

m	Zu streichende Literaturausschnitte
0,3,6,9	A - H
1,4,7	G - N
2,5,8	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 A practical ... system does not make perfect match decisions and can make two basic types of errors: (i) False Match: the ... system incorrectly declares a successful match between the input pattern and a nonmatching pattern in the database (in the case of identification/screening) or the pattern associated with an incorrectly claimed identity (in the case of verification). (ii) False Non-match: the ... system incorrectly declares failure of match between the input pattern and a matching pattern in the database (identification/screening) or the pattern associated with the correctly claimed identity (verification). It is more informative to report the system accuracy in terms of a Receiver Operating Characteristic (ROC) curve.

B 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.

C 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.

D 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. Zernike moment 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).

E A curve pyramid and an image pyramid are built in a similar way. Filtering, followed by subsampling, are applied to the original signal. Thus, each pyramid level (k) holds a smoothed and subsampled version of the signal at the level below $(k-1)$. ...
...At level $k+1$, the chain-code of node i, C_i^{k+1}, is the average between the chain-codes of nodes $2i$ and $2i+1$ at level k:

$$C_i^{k+1} = [(C_{2i}^k + C_{2i+1}^k + Off)/2]_{\mathrm{mod}8}, \quad 0 \le i < N_{k+1}, \tag{3}$$

where Off takes the following values:

$$Off = \begin{cases} 0 & \text{if } |C_{2i}^k - C_{2i+1}^k| < 4, \\ 8 & \text{if } |C_{2i}^k - C_{2i+1}^k| > 4. \end{cases}$$

F As mentioned in the Introduction, the chain coded description is very useful to speed up matching time for contour images. However, for the contour images which are very complicated in shape, it is very difficult to find the corresponding contour image before examining the similarity between the two contour images. To avoid this intricate problem, in the proposed method, only registered contour images are described by chain codes (see Fig. 12) [14].

G Syntactic analysis is inspired by the phenomenon that composition of a natural scene is an analog to the composition of a language, that is, sentences are built up from phrases, phrases are built up from words and words are built up from alphabets, etc. [67]. In syntactic methods, shape is represented by a set of predefined primitives. The set of predefined primitives is called the codebook and the primitives are called codewords. ...The matching between shapes can use string matching by finding the minimal number of edit operations to convert one string into another.

H ...The image is partitioned into piecewise smooth regions in which the mean is the estimate of brightness, and the standard deviation is an overestimate of noise level. The prior probability of the noise level functions is learned by simulating the digital camera imaging process and are used to help estimate the curve correctly where there is missing data.
Since separating signal and noise from a single input is underconstrained, it is in theory impossible to completely recover the original image from the noise contaminated observation. The goal of image denoising is to preserve image features as much as possible while eliminating noise. ...

I 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.

J ... operator [8] is a second derivative operator that is used to detect the zero-crossings of image intensity and often yields more exact edge detecting result. Unfortunately, it is not used frequently in computer vision since its operator involves two derivatives which is apt to be affected by noise. Therefore, the Laplacian of Gaussian (LoG) [2] was developed, which is desirable to filter out the noise with a Gaussian filter before detecting edges with the Laplacian operator. However, it is hard to imagine that an optimal edge detector can be set up by this way.

K Zernike moments 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.

L 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.

M ... In our face authentication system, the isodensity contours has been introduced to differentiate between the facial features. These isodensity contours can be transformed into chain codes. By using these coded isodensity contours, remarkable improvement in the processing performance can be expected in terms of the processing time and memory requirements. ¿From the computer simulation performed using images of 50 people, it turned out clear that the processing time was decreased to approximately one-seventh compared to the conventional method. With respect to memory requirement, it was reduced to a quarter.

N Automated segmentation of images has been considered an important intermediate processing task to extract semantic meaning from pixels. We propose an integrated approach for image segmentation based on a generative clustering model combined with coarse shape information and robust parameter estimation. The sensitivity of segmentation solutions to image variations is measured by image resampling. Shape information is included in the inference process to guide ambiguous groupings of color and texture features. Shape and similarity-based grouping information is combined into a semantic likelihood map in the framework of Bayesian statistics. Experimental evidence shows that semantically meaningful segments are inferred even when image data alone gives rise to ambiguous segmentations.

O Image denoising algorithms often assume an additive white Gaussian noise (AWGN) process that is independent of the actual RGB values. Such approaches cannot effectively remove color noise produced by todays CCD digital camera. In this paper, we propose a unified framework for two tasks: automatic estimation and removal of color noise from a single image using piecewise smooth image models. We introduce the noise level function (NLF), which is a continuous function describing the noise level as a function of image brightness.We then estimate an upper bound of the real NLF by fitting a lower envelope to the standard deviations of per-segment image variances. For denoising, the chrominance of color noise is significantly removed by projecting pixel values onto a line fit to the RGB values in each segment. Then, a Gaussian conditional random field (GCRF) is constructed to obtain the underlying clean image from the noisy input. Extensive experiments are conducted to test the proposed algorithm, which is shown to outperform state-of-the-art denoising algorithms.

P The ... operator-based edge detectors localize edges with the zero-crossings of the high-frequency components of image. One problem arising from this is that the noise contained in the high-frequency components will yield false zero-crossings. Noting that the amplitudes of high-frequency components of edges are relatively larger than that of noise, we may remove the low amplitudes of noise by thresholding the high-frequency components of an image.

Q The semantic abstraction from pixels to objects in computer vision requires grouping low-level image information into coherent groups or segments. This segmentation stage in image interpretation is of prime importance in low and mid-level vision since it substantially reduces the information content of images while preserving essential information about objects. The segmentation process is implemented by a mixture modeling approach in this paper, i.e., we use the Parametric Distributional Clustering (PDC) [13] framework and we combine it with coarse shape information. Data groups are represented by continuous mixture models for color and texture feature distributions, whereas individual image sites are characterized by local histograms of feature measurements.

R Reliable person identification is an important problem in diverse businesses. ... Identification based on distinctive personal traits has the potential to become an irreplaceable part of any identification system. While successful in some niche markets, the biometrics technology has not yet delivered its promise of foolproof automatic identification. With the availability of inexpensive biometric sensors and computing power, it is becoming increasingly clear that widespread usage of biometric person identification is being stymied *(dt.verhindert)* by our lack of understanding of three fundamental problems: (i) How to accurately and efficiently represent and recognize biometric patterns? (ii) How to guarantee that the sensed measurements are not fraudulent *(dt. missbraucht)* ? and (iii) How to make sure that the application is indeed exclusively using pattern recognition for the expressed purpose?

S 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.

T A minutiae-based template is a very compact representation of a fingerprint image, and for a long time, it has been assumed that it did not contain enough information to allow the reconstruction of the original fingerprint. This work proposes a novel approach to reconstruct fingerprint images from standard templates and investigates to what extent the reconstructed images are similar to the original ones (that is, those the templates were extracted from). The efficacy of the reconstruction technique has been assessed by estimating the success chances of a masquerade attack against nine different fingerprint recognition algorithms. The experimental results show that the reconstructed images are very realistic and that, although it is unlikely that they can fool a human expert, there is a high chance to deceive state-of-the-art commercial fingerprint recognition systems.

6 Welche Ausschnitte gehören zu folgenden Titel ?

1 Review of shape representation and description techniques

Ausschnitt(e): .....

Begründung(en): .....

2 Automatic Estimation and Removal of Noise from a Single Image

Ausschnitt(e): .....

Begründung(en): .....

3 Fingerprint Image Reconstruction from Standard Templates

Ausschnitt(e): .....

Begründung(en): .....

4 Robust Image Segmentation Using Resampling and Shape Constraints

Ausschnitt(e): .....

Begründung(en): .....

5 Laplacian Operator-Based Edge Detectors

Ausschnitt(e): .....

Begründung(en): .....

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

Ausschnitt(e): .....

Begründung(en): .....

7 Color image segmentation based on homogram thresholding and region merging

Ausschnitt(e): .....

Begründung(en): .....

8 Fast template matching algorithm for contour images based on its chain coded description applied for human face identification

Ausschnitt(e): .....

Begründung(en): .....

9 Sketched Symbol Recognition using Zernike Moments

Ausschnitt(e): .....

Begründung(en): .....

10 Biometrics: A Grand Challenge

Ausschnitt(e): .....

Begründung(en): .....