

I (14):

II (20):

III (16):

Schriftliche Prüfung aus Grundlagen der Digitalen Bildverarbeitung WS 2010/2011

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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. 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

$$\begin{array}{ll} \text{Matrix} & A = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \quad A = [a \ b; \ c \ d]; \text{ Spaltenvektor} & x = \begin{pmatrix} y \\ z \end{pmatrix} \quad x = [y; z] \\ \text{Zeilenvektor} & e = \begin{pmatrix} f & g \end{pmatrix} \quad e = [f \ g] \end{array}$$

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Command Reference

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

h = fspecial('laplacian')

returns a 3-by-3 filter approximating the shape of the two-dimensional Laplacian operator.

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=imhist(I)

displays histogram of image data I.

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 = imerode(IM,SE)

erodes the grayscale, binary, or packed binary image IM, returning the eroded image IM2. The structuring element, 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.

SE = strel('disk',R)

creates a flat, disk-shaped structuring element, where R specifies the radius.

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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();

Begründung:

1. = conv2(, 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. = imhist(I);

Begründung:

7. = imdilate(, strel('disk', 3));

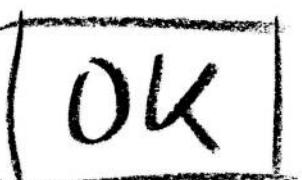
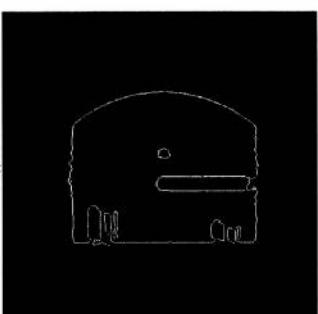
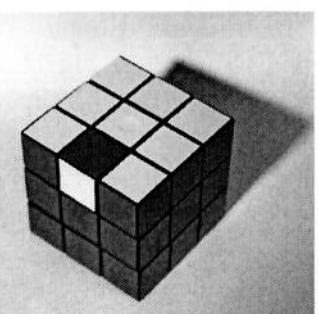
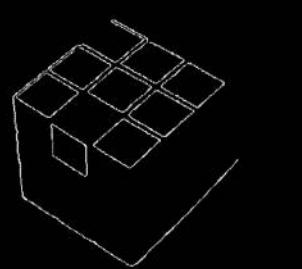
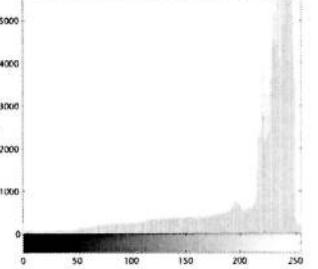
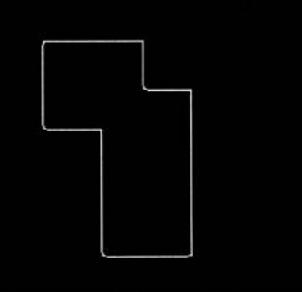
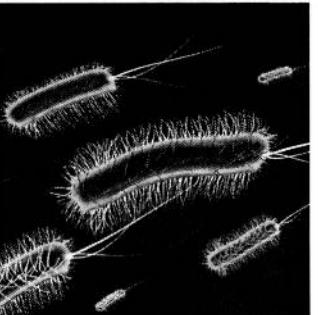
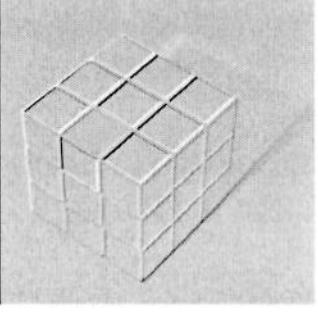
Begründung:

8. =imerode(, strel('disk', 20));

Begründung:

9. = log1p(abs(fftshift(fft2(Q))));

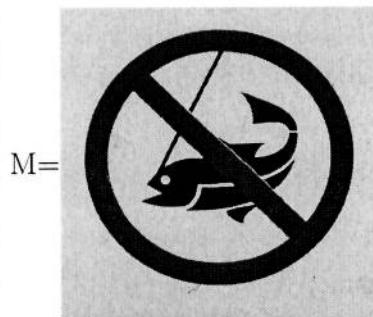
Begründung:

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

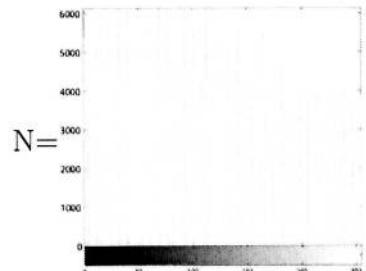
Grauwertbilder

0

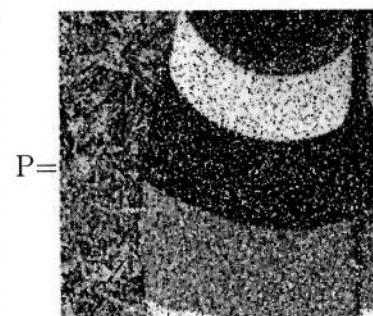
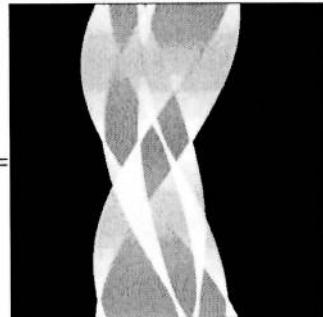
255



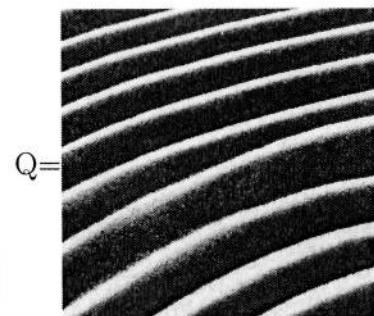
M=



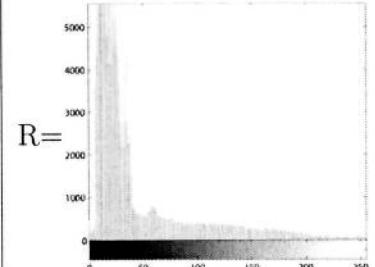
O=



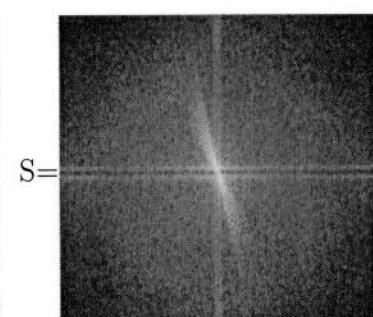
P=



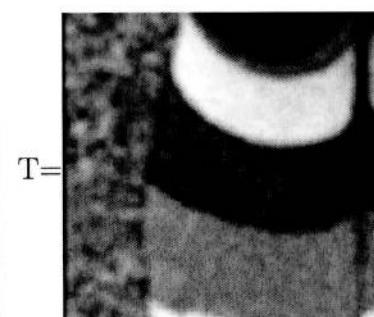
Q=



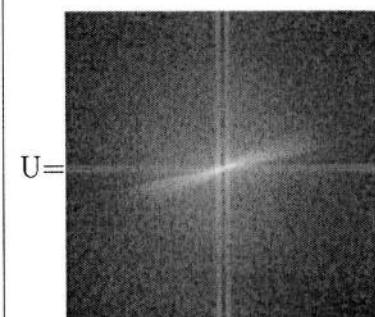
R=



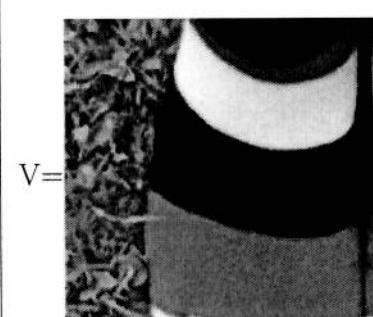
S=



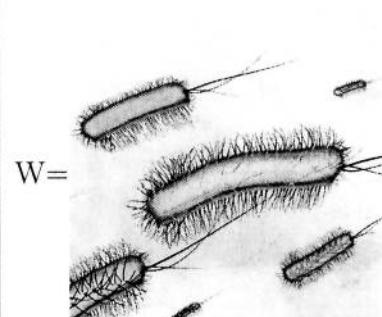
T=



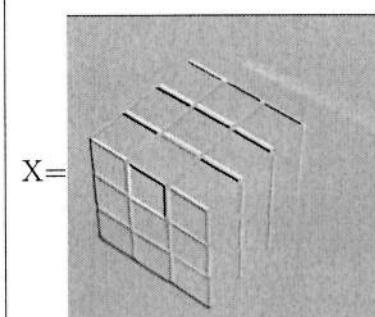
U=



V=



W=



X=

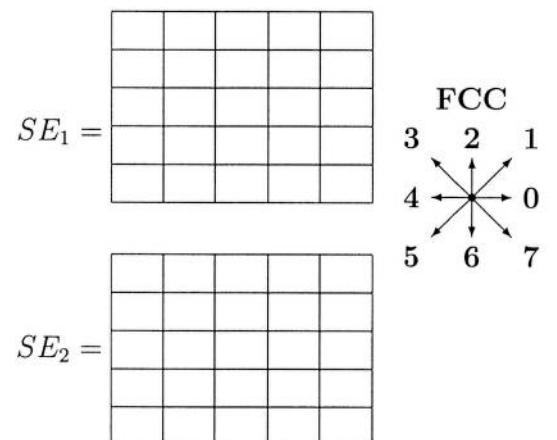
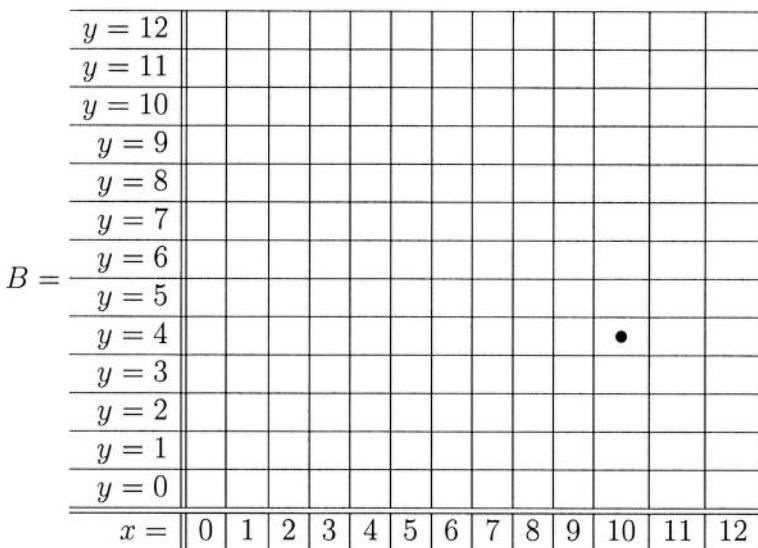
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Teil II: Mathematisches Nachvollziehen (20)

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

1 Diskrete Geraden und Morphologie (5)

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: $c^n dc^n d \dots$
2. Wählen Sie c, d als jene zwei aufeinanderfolgenden Ziffern Ihrer Matrikelnummer M , die für kleinstes k die folgende Bedingung erfüllt: $M_i < 7$ und $|M_{i+1} - M_i| = k, k = 1, 2, \dots$
 $c = M_i = \square$, $d = M_i + (M_{i+1} - M_i)/k = \square$.
3. Den Startpixel tragen Sie im Bild so ein (\bullet), dass die Gerade das Bildfenster quert. Markieren Sie dann jene Pixel der diskreten Geraden $c^3dc^3d\dots$ im Bild durch \bullet , die nach dem Code d erreicht werden.
4. Mit welchem morphologischen Operator und welchem Strukturelement (SE_1) werden die Lücken der Gerade geschlossen? $B_1 = \boxed{\quad} (B, SE_1)$, markiere Pixel mit \circ .
5. Mit welchem morphologischen Operator und welchem SE_2 werden danach falsche Linienstücke¹ eliminiert? $B_2 = \boxed{\quad} (B_1, SE_2)$, markiere gelöschte Pixel mit X.



¹andere Richtungen, Noise

2 Hough-Transformation (5)

1. Zwei Parameter bestimmen den Inhalt des Hough-Akkumulators:

$$a = \max\{M_i | i = 1, \dots, 7\} = \square \quad b = \begin{cases} a - 1 & \text{if median } \{M_i | i = 1, \dots, 7\} = \square < 5 \\ a - 2 & \text{sonst} \end{cases} = \square .$$

2. Im Hough-Akkumulator werden die drei Winkel $\theta \in \{0^\circ, 90^\circ, 135^\circ\}$ und pro Winkel drei Abstände $r =$ 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	$r_3 < r$
$\theta = 0^\circ$		$r_1 = 1$		$r_2 = a$		$r_3 = a + 3$	
$H(\theta, r) =$	0	b	3	$b + 1$	3	b	0
$\theta = 90^\circ$		$r_1 = 1$		$r_2 = b$		$r_3 = b + 3$	
$H(\theta, r) =$	0	a	3	$a + 1$	3	a	0
$\theta = 135^\circ$		$r_1 = \frac{1-a}{\sqrt{2}}$	3	$r_2 = \frac{b-a}{\sqrt{2}}$	3	$r_3 = \frac{b-1}{\sqrt{2}}$	0
$H(\theta, r) =$	0	4		5		4	

3. Die Hesse'schen Normalform $r =$ lässt sich für die drei Winkel² in ganz-zahligen Koordinaten vereinfachen:

θ	$f(x, y)$	$=$	$g(r)$
0°		$=$	
90°		$=$	
135°		$=$	

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

² $\sin 135^\circ = 1/\sqrt{2}$

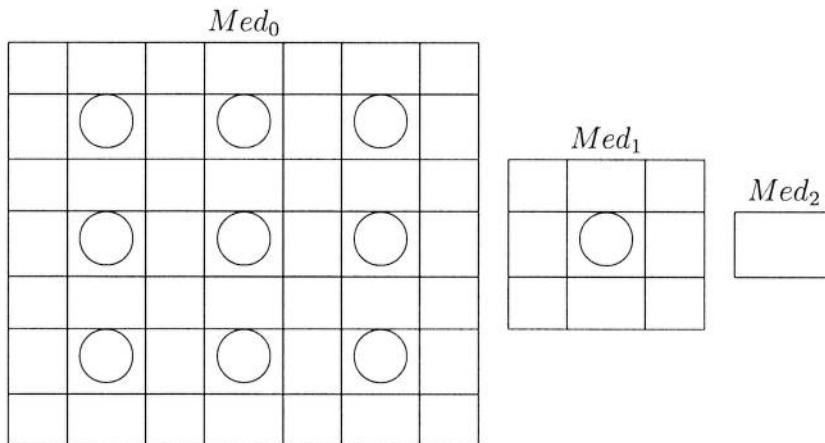
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3 Medianpyramide (5 P)

1. Die Häufigkeit der Grauwerte 1 bis 7 der Grundebene Med_0 wird durch Ziffern Ihrer Matrikelnummer bestimmt: $H_0(g) = M_g, g = 1, 2, \dots, 7$. Der Rest der 7×7 -Grundebene ist mit 0 aufgefüllt.

$g =$	0	1	2	3	4	5	6	7
$H_0(g) =$								
$K_0(g) =$								49
$H_1(g) =$								
$CC(g + 0.5) =$								x

2. Zur Bestimmung des Median dient das kumulative Histogramm $K_0(g) = \sum_{i=0}^g H_0(i)$.
3. Das zentrale Element von Med_0, Med_1, Med_2 wird mit dem Median aller 49 Pixel der Grundebene Med_0 gefüllt.
4. Das Histogramm der Ebene 1 der $3 \times 3/4$ Medianpyramide wird durch $H_1(g) \approx [H_0(g)/5]$ ermittelt. Beachte, dass 'ausgewogen' gerundet wird und die Gesamtpixelanzahl der Ebene 1 genau 9 sein und der Median vorkommen muss!
5. Als Reduktionsfunktion soll der Median des 3×3 Reduktionsfensters dienen.
6. Verteile die Grauwerte der Histogramme H_0, H_1 so auf die Ebenen der Medianpyramide, dass
- der Median jedes 3×3 Reduktionsfensters genau dem Elternpixel entspricht;
 - gleiche Grauwerte innerhalb jeder Ebene möglichst eine einfach 4-zusammenhängende Region bilden.



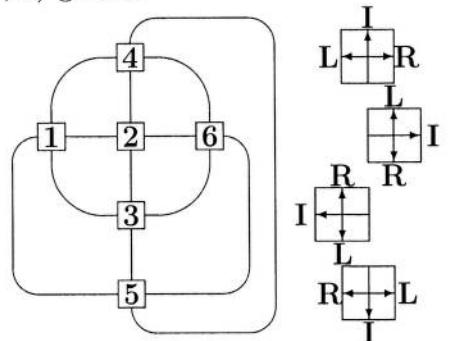
7. Bestimme die Anzahl der 4-Zusammenhangskomponenten $CC(t) = |\{Med_0(x, y) < t\}|$ für $t = 0.5, 1.5, \dots, 6.5$ (in obiger Tabelle 1. in Zeile $CC(g + 0.5)$ eintragen).

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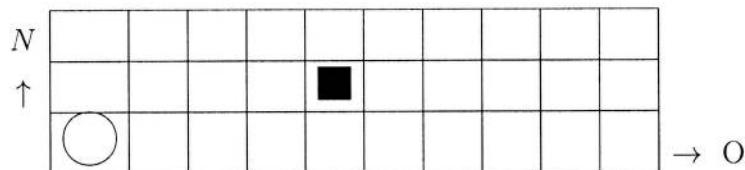
4 Minimale Pfade mit Würfeln (5)

Ein Würfel wird im linken unteren Eck eines 3×10 Bildrasters gelegt. Die oben aufscheinende Augenzahl wird in dem darunterliegenden Pixel eingetragen. Durch Kippen des Würfels über eine seiner 4 Kanten kommt der Würfel auf dem jeweils benachbarten Pixel zu liegen. Auch hier wird die nun oben liegende Augenzahl im Pixel eingetragen. Durch wiederholtes Kippen wird ein Pfad von 4-benachbarten Pixeln mit den Augenzahlen des Würfels (1,2,...,6) gefüllt.

Die Struktur des Würfels ist durch seinen Aspectgraphen festgelegt, wobei nur die jeweils oben liegende Augenzahl sichtbar ist und ein einmaliges Kippen durch eine Kante ausgedrückt wird. Eine Folge von Kippbewegungen (z.B. 3,2,4,5,6,3) wird durch eine RULI-chain beschrieben. Das Beispiel startet mit 3 ostwärts: $I^3 RL$ korrespondiert $\begin{array}{|c|c|c|c|c|} \hline 3 & 2 & 4 & 5 & \\ \hline & & 6 & 3 & \\ \hline \end{array}$. Entsprechende Bewegungen (L...links, R...rechts, I...in dieselbe Richtung) erfolgen auch auf dem Pixelraster.



1. Platziere einen Würfel mit der Augenzahl $\operatorname{argmin}\{M_i | i = 1, 2, 3, \dots, 6\} = \bigcirc$ (bei Mehrdeutigkeiten die vordere Ziffer) im linken unteren Eck des 3×10 Feldes und trage die Augenzahl im markierten Feld ein. Von hier starten Pfade in zwei Richtungen N und O.
2. Sie haben die Aufgabe, jede der 29 restlichen Positionen durch schrittweises Kippen des Würfels und Eintragen der oben liegenden Augenzahl zu füllen. Alle Pfade beginnen im linken unteren Feld und führen jeweils zu Pixeln, die weiter rechts (O) oder weiter oben (N) liegen. Der durch \blacksquare gekennzeichnete Pixel wird ausgelassen. Jeder Pixel oberhalb und rechts des Startpixels hat in seinen Paden ein oder zwei Vorgänger!
3. Im Falle von zwei Vorgängern wird nur jener Pfad fortgesetzt, der im Pixel die kleinere Augenzahl speichert. Die Lösung wird erleichtert, wenn die Kante des unterbrochenen Pfades markiert wird.



4. Auf welchem Pfad wird der Würfel vom Startpunkt zum rechten oberen Pixel bewegt?

Folge der Augenzahlen:

korrespondierende RLI-chain:

.....

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Teil III: Selektion von Literatur (16)

In Abschnitt ?? finden Sie 10 Titel wissenschaftlicher Publikationen. In Abschnitt ?? 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 dazugehörigen 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 One of the advantages of the ... is that they provide a "spatial view" of the image. One way to represent a ... consists of associating a vertex at each region and an edge at each pair of adjacent regions. By definition, this region ... provides a simple-connectivity view of the image, such as this illustrated in Fig. 4(b). Beyond this simple-connectivity view, this ... gives also a high-level connectivity view of the image. Thus, considering the Fig. 4, we can observe that regions 1 and 2 are adjacent, likewise regions 2 and 3 are adjacent, that leads us to note that regions 1 and 3 present a second-order connectivity relationships. In fact the simple-connectivity view contains inherently all high-level connectivity relationships of the image, moreover it can be considered as the dual of the regions partitioning of the image (see Fig. 5).
- B 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 ...

C ... is widely used for contrast enhancement in a variety of applications due to its simple function and effectiveness. Examples include medical image processing and radar signal processing. One drawback of the ... can be found on the fact that the brightness of an image can be changed after the ... , which is mainly due to the flattening property of the Thus, it is rarely utilized in consumer electronic products such as TV where preserving original input brightness may necessary in order not to introduce unnecessary visual deterioration. This paper proposes a novel extension of ... to overcome such drawback of the The essence of the proposed algorithm is to utilize independent ... separately over two subimages obtained by decomposing the input image based on its mean with a constraint that the resulting equalized subimages are bounded by each other around the input mean.

D ... detectors of some kind, particularly step ..., have been an essential part of many computer vision systems. The ... process serves to simplify the analysis of images by drastically reducing the amount of data to be processed, while at the same time preserving useful structural information about object boundaries. There is certainly a great deal of diversity in the applications of ... detection, but it is felt that many applications share a common set of requirements. These requirements yield an abstract edge detection problem, the solution of which can be applied in any of the original problem domains.

E The method is an extension of the ... data structure described in [25]. The ... holds at the point (x, y) in the image the sum of all the pixels contained in the rectangular region defined by the top-left corner of the image and the point (x, y) . This image allows to compute the sum of the pixels on arbitrary rectangular regions by considering the 4 ... values at the corners of the region - in other words in (very short) constant time independent of the size of the region. In order to extract ... over arbitrary rectangular regions, in the ... we build for each bin of the ... an ... counting the cumulative number of pixels falling into that bin. Then by accessing these ... we can immediately compute the number of pixels in a given region which fall into every bin, and hence we obtain the ... of that rectangular region.

F Planar curves are described by information about corners integrated over various levels of resolution. The detection of corners takes place on a digital representation. To compensate for ambiguities arising from sampling problems due to the discreteness, results about the local behavior of curvature extrema in continuous scale-space are employed.

G We present a novel method to obtain the three-dimensional Euclidean distance transformation (EDT) in two scans of the image. The shortest path can be extracted based on the distance maps using the minimum value tracing. The EDT is obtained correctly and efficiently in a constant time for arbitrary types of images, including the existence of obstacles. By adopting the new dynamically rotational mathematical morphology, we not only guarantee the collision-free in the shortest path, but also reduce the time complexity dramatically.

H Assume that an arbitrarily-shaped object moves from a starting point to a destination point in a finite space with arbitrarily-shaped obstacles in it. We relate this model to mathematical morphology using the following strategy:

- (1) The finite space consists of free regions as foreground and obstacles as "forbidden" areas with value "-1" and the moving object is modeled as the structuring element;
- (2) Set the destination point to be "0";
- (3) Apply a morphological erosion to the free regions, followed by a distance transformation on the region with the grown obstacles excluded, and then trace the distance map from any starting point to its neighbor of the minimum distance until the destination point is reached.

I A second issue, inherent in the use of . . . , is the loss of spatial information. This issue has been addressed by several works. In [26] the authors introduce a new similarity measure between the template and image regions, which replaces the original Bhattacharyya metric. This measure takes into account both the intensities and their position in the window. The measure is further computed efficiently by using the Fast Gauss Transform. In [12], the spatial information is taken into account by using oriented kernels - this approach is additionally shown to be useful for wide baseline matching. Recently, [4] has addressed this issue by adding the spatial mean and covariance of the pixel positions who contribute to a given bin in the . . . - naming this approach as spatiograms.

J For a given video, each frame is segmented into a number of regions using region segmentation technique. Then, Region Adjacency Graph (RAG) is obtained by converting each region into node, and spatial relationships among regions into edges [4, 5]. RAG is good for representing spatial relationships among nodes indicating the segmented regions. However, it cannot represent temporal characteristics of video. We propose a new graph-based data structure for video, Spatio Temporal Region Graph (STRG) which is temporally connected RAGs. The STRG can handle both temporal and spatial characteristics of video.

K These three conditions determine the good arrangement of vertices in sets of nearly similar vertices, that implies also regions underlying of vertices. Thus, the first condition implies that two adjacent regions can be merged only if they are closed enough. Likewise, the second and the third condition stipulate that this merging can not be performed at the disadvantage of sets of regions already done. That is to say local and global homogeneity criteria prevail to punctual homogeneity criterion. These three criteria enable us to gather the current region to a set of regions being processed, not because only one region of this set is adjacent and sufficiently similar to the current one, but above all because most of adjacent regions already belonging to the set of regions being processed, are also similar to the current one.

L ... can be used to represent quite generic objects. For example, the appearance models for the individual parts can be a blob of some color and orientation, or capture the response of local oriented filters. The connections between parts can encode generic relationships such as close to, to the left of, or more precise geometrical constraints such as ideal joint angles. Since both the part models and the relationships between parts can be generic, pictorial structures provide a powerful framework. Suppose we want to model the appearance of the human body. It makes sense to represent the body as an articulated object, with joints connecting different body parts. With ... we can use a coarse model, consisting of a small number of parts connected by flexible joints. The combination of simple appearance models for the parts and structural relations between parts provides sufficient context to find the human body as a whole, even when it would be difficult to find generic parts such as lower-leg or upper-arm on their own.

M In this work we propose a new graph-based data structure, ... representing spatial and temporal relationships among objects in a video. After an ... is construed, it is decomposed into its subgraphs called object graphs (OGs), which represent each semantic object in a video sequence. Since an STRG provides not only spatial view of individual frame but also temporal relationships between consecutive frames, we can detect video objects more accurately. For unsupervised learning, we cluster similar OGs into a group, in which we match two OGs. For this ..., we introduced a new distance measure, extended graph edit distance (EGED) which can handle temporal characteristics of OGs. For actual clustering, we employed a model-based EM clustering with EGED. It can cluster video objects semantically.

N Dilation by disk structuring elements correspond to isotropic swelling or expansion algorithms common to binary image processing. Dilation by small squares (3×3) is a neighborhood operation easily implemented by adjacency connected array architectures (grids) and is the one many image processing people know by the name "fill," "expand," or "grow." Some example dilation transformations are illustrated in Figs. I and 2. Neighborhood connected image processors such as CLIP, Cytocomputer, and MPP can implement some dilations (not all) by structuring elements larger than the neighborhood size by iteratively dilating with a sequence of neighborhood structuring elements.

O Another example which shows the limitation of the ... is illustrated in Fig. 4, where the first image is a given original image F16 and the second one is the result of The respective histograms of those images are shown in Fig. 5 and the transform function associated with (3) is depicted in Fig. 6. First, unnatural enhancement can be seen from this example around the cloud after the In other words, one would perceive totally different visual recognition around the cloud after the Moreover, if we investigate closely the images before and after the ..., one can observe that the contrasts around the letters and the emblem on the airplane are degraded. The reason for such limitations of the ... for this example can be easily understood from Fig. 6.

P In two dimensions it was shown that marking ... points at maxima of gradient magnitude in the gradient direction is equivalent to finding zero-crossings of a certain nonlinear differential operator. It was shown that when ... contours are locally straight, highly directional operators will give better results than operators with a circular support. A method was proposed for the efficient generation of highly directional masks at several orientations, and their integration into a single description. Among the possible extensions of the work, the most interesting unsolved problem is the integration of different ... detector outputs into a single description. A scheme which combined the ... and ridge detector outputs using feature synthesis was implemented, but the results were inconclusive.

- Q In practice, dilations and erosions are usually employed in pairs, either dilation of an image followed by the erosion of the dilated result, or image erosion followed by dilation. In either case, the result of iteratively applied dilations and erosions is an elimination of specific image detail smaller than the structuring element without the global geometric distortion of unsuppressed features. For example, opening an image with a disk structuring element smooths the contour, breaks narrow isthmuses, and eliminates small islands and sharp peaks or capes. Closing an image with a disk structuring element smooths the contours, fuses narrow breaks and long thin gulfs, eliminates small holes, and fills gaps on the contours.
- R A multiresolution description of planar curves using corners and the curve pyramid has 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 $63.4^\circ(108.4^\circ)$ and the distance from one corner to the next is a receptive field (a receptive region of three cells).
- S ... In our ... 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.
- T Research in object recognition is increasingly concerned with the ability to recognize generic classes of objects rather than just specific instances. In this paper, we consider both the problem of recognizing objects using generic part-based models and the problem of learning such models from example images. Our work is motivated by the ... representation introduced by Fischler and Elschlager (1973) thirty years ago, where an object is modeled by a collection of parts arranged in a deformable configuration. Each part encodes local visual properties of the object, and the deformable configuration is characterized by spring-like connections between certain pairs of parts. The best match of such a model to an image is found by minimizing an energy function that measures both a match cost for each part and a deformation cost for each pair of connected parts.

6 Welche Ausschnitte gehören zu folgenden Titel ?

- 0 Regions Adjacency Graph Applied to Color Image Segmentation
Ausschnitt(e):
Begründung(en):
- 1 Pictorial Structures for Object Recognition
Ausschnitt(e):
Begründung(en):
- 2 Robust Fragments-based Tracking using the Integral Histogram
Ausschnitt(e):
Begründung(en):
- 3 A Computational Approach to Edge Detection
Ausschnitt(e):
Begründung(en):
- 4 Image Analysis Using Mathematical Morphology
Ausschnitt(e):
Begründung(en):
- 5 Clustering of Video Objects by Graph Matching
Ausschnitt(e):
Begründung(en):
- 6 Three-dimensional Euclidean distance transformation and its application to shortest path planning
Ausschnitt(e):
Begründung(en):
- 7 Fast template matching algorithm for contour images based on its chain coded description applied for human face identification
Ausschnitt(e):
Begründung(en):
- 8 Contrast enhancement using brightness preserving bi-histogram equalization
Ausschnitt(e):
Begründung(en):
- 9 A Syntactic Approach to Scale-Space-Based Corner Description
Ausschnitt(e):
Begründung(en):