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

Schriftliche Prüfung aus Grundlagen der Digitalen Bildverarbeitung WS 2010/2011

Walter G. Kropatsch, Nicole M. Artner

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

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

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

Teil I: Interpretation von Bildoperationen (14)

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

Allgemeines

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

Matlab Referenz

Notationen

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

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

Command Reference

`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.

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

`J = histeq(I,n)`
transforms the intensity image I, returning in J an intensity image with n discrete gray levels. A roughly equal number of pixels is mapped to each of the n levels in J, so that the histogram of J is approximately flat. (The histogram of J is flatter when n is much smaller than the number of discrete levels in I.) The default value for n is 64

`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 = 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.

`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.

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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(C);`

   Begründung: ....

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

   Begründung: ....

2. ☐ `= 1-im2bw(` ☐ `,200/255);`

   Begründung: ....

3. ☐ `= 1-im2bw(` ☐ `,10/255);`

   Begründung: ....

4. ☐ `= imhist(histeq(N));`

   Begründung: ....

5. ☐ `= imhist(R);`

   Begründung: ....

6. ☐ `= imopen(` ☐ `,strel('disk',10));`

   Begründung: ....

7. ☐ `= imerode(` ☐ `,strel('disk',15));`

   Begründung: ....

8. ☐ `= "Hough-Transform"(E);`

   Begründung: ....

9. ☐ `= bwdist(` ☐ `);`

   Begründung: ....

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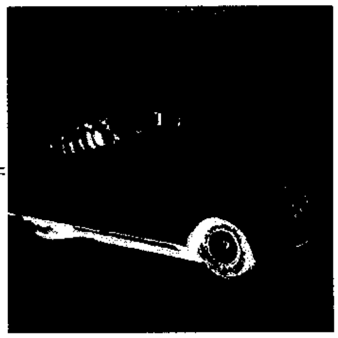
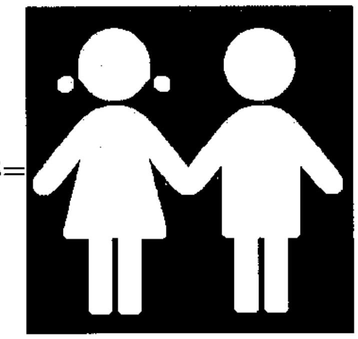
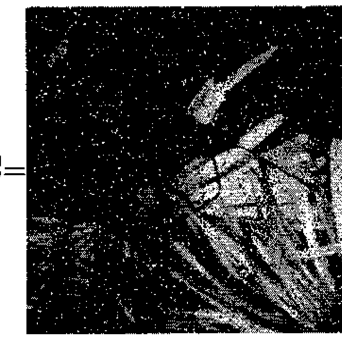
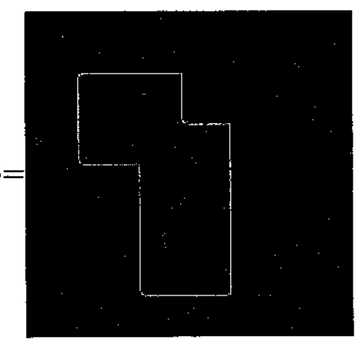
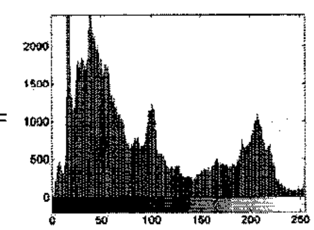
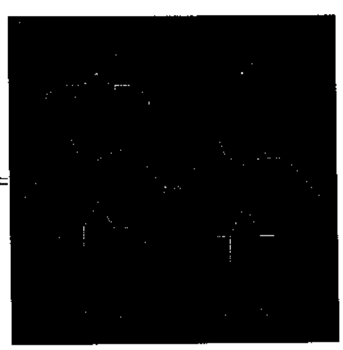
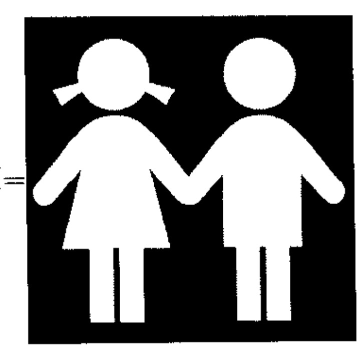
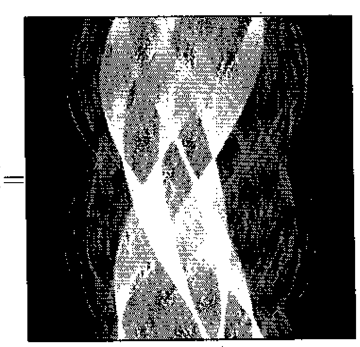
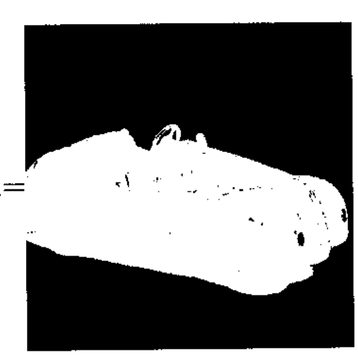
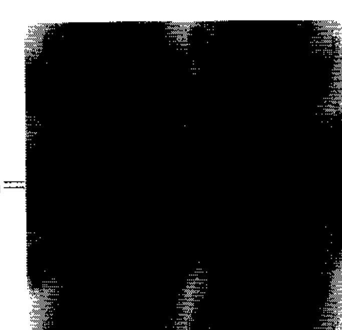
Binärbilder		Grauwertbilder
A= 	B= 	C= 
D= 	E= 	F= 
G= 	H= 	I= 
J= 	K= 	L= 

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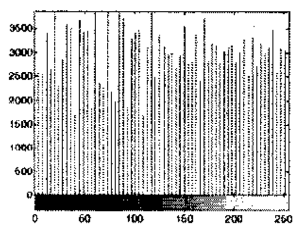
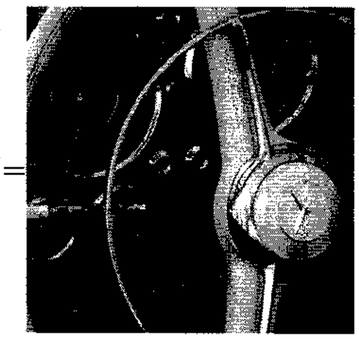
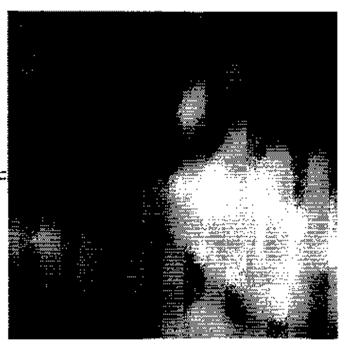
Grauwertbilder

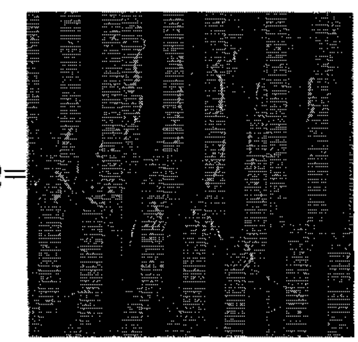
0  255

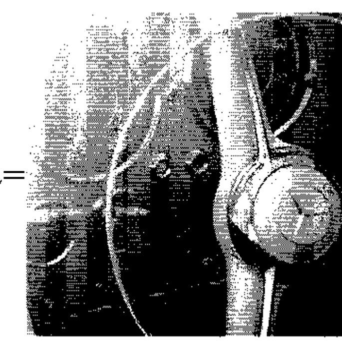
M= 

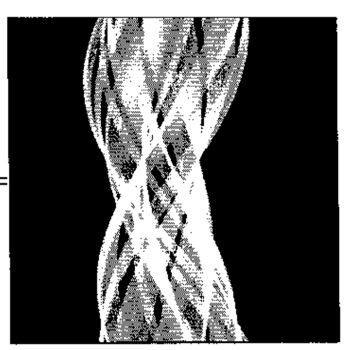
N= 

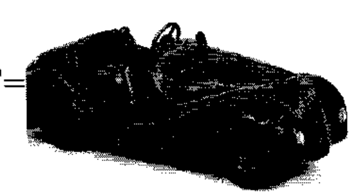
O= 

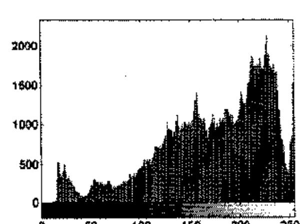
P= 

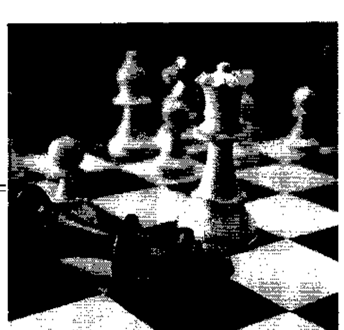
Q= 

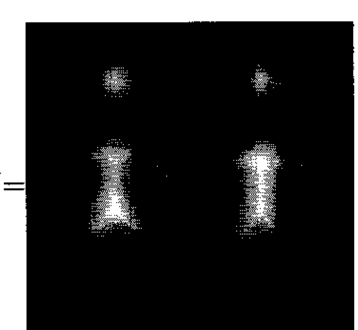
R= 

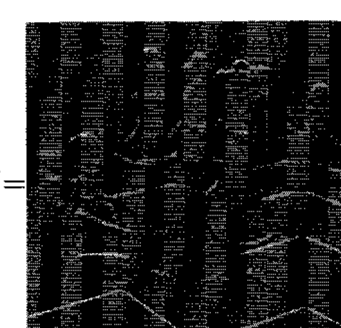
S= 

T= 

U= 

V= 

W= 

X= 

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Teil II: Mathematisches Nachvollziehen (20)

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

1 Hough-Transformation (5)

1. Sei $S = \mathrm{mod}(M, 3) + 5 = \square$ der 4-Abstand einer Schar von Linien.
2. Die Linienschar sei wie folgt definiert:

$$B(x,y) = \begin{cases} 1 & \text{wenn } \mathrm{mod}(x-y, S) = 0, x \in [0,10], y \in [0,5] \\ 0 & \text{sonst} \end{cases}$$

3. Zeichnen Sie alle Punkte $B(x,y) = 1$ als x im folgenden Bild zusätzlich zu den zwei Störpixeln "*" ein:

$y = 5$											
$y = 4$											
$y = 3$					*						
$y = 2$					*						
$y = 1$											
$y = 0$											
$x =$	0	1	2	3	4	5	6	7	8	9	10

4. Bestimme die Hough-Transformation für alle Punkte ($B(x,y) = 1$) mit der Hesse'schen Normalform $\boxed{r = \qquad}$ und $\theta \in \{0^0, 45^0, 90^0, 135^0\}$. Zuerst werden die $r-$Werte für die vier Winkel[1] benötigt:

θ	$r(x,y)$	Werte für r bzw. $r\sqrt{2}$ für alle (x,y) mit $B(x,y) = 1$
0^0	$r =$	
45^0	$r = (\qquad)/\sqrt{2}$	
90^0	$r =$	
135^0	$r = (\qquad)/\sqrt{2}$	

5. Trage die Anzahl der Punkte in den quantisierten Hough-Akkumulator $H(\theta, r)$ ein (ergänze Spalten für benötigte Werte von r).

$r \in$				0	1	2	3	4	5	6	7	8	9	10		
$r\sqrt{2} \in$				0	1		2	3		4	5	6		7		
$\theta = 0^0$																
$\theta = 45^0$																
$\theta = 90^0$																
$\theta = 135^0$																

6. Welche Geraden werden erkannt? Formel: ....

[1] $\cos 45^o = \sin 45^o = \sin 135^o = 1/\sqrt{2}$

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2 Morphologische Transformation zu Punktraster (5)

1. Sei $S = 2 \cdot \text{mod}(M, 3) + 4 = \square$ der 4-Abstand zwischen den Linien eines Rasters.
2. Das Raster sei wie folgt definiert:

$$R(x,y) = \begin{cases} 1 & \text{wenn } \text{mod}(x-y, S) = 0 \text{ oder } \text{mod}(x+y, S) = 0 \\ 0 & \text{sonst} \end{cases}$$

3. Zeichnen Sie alle Linienpixel $R(x,y) = 1$ als x im folgenden Bild B ein, das bereits einige Störpixel enthält:

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

Strukturelemente

					D				
		C							

		E							
					F				

4. Dieses Binärbild B soll in ein Punktgitter P umgewandelt werden, das nur die Kreuzungspunkte innerhalb des Rasters enthält und die Störpixel löscht. Dazu stehen die morphologischen Operationen ERODE $\ominus$, DILATE $\oplus$, OPEN $\circ$ und CLOSE $\bullet$ mit entsprechend zu wählenden Strukturelementen zur Verfügung. Ausserdem können Zwischenresultate mit den logischen Operatoren ODER $\vee$ und UND $\wedge$ verknüpft werden.

5. Strukturelemente können oben frei durch x definiert/ergänzt werden, wobei der Referenzpixel mit einem Buchstaben bezeichnet wird, der auch in den Operationen als Name des Strukturelements dient. Z.B. $Z_1 = B \oplus C$. Alle zusätzlichen Pixel des Strukturelements werden durch x eingetragen.

6. Welche Operationen sind notwendig, um aus dem gestörten Binärbild B das Punktgitter P zu produzieren (bis zu 2 Zwischenschritte können angegeben werden.)?

   1. $Z_1 =$ ....
   2. $Z_2 =$ ....
   3. $P =$ ....

7. Wieviele Punkte $P(x,y) = 1$ enthält $|P| = \square$?

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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

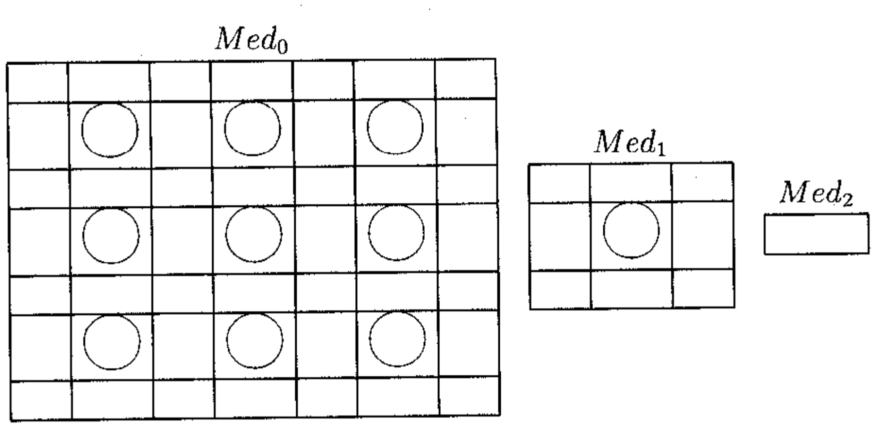
2. Zur Bestimmung des Median dient das kumulative Histogramm $K_0(g) = \sum_{i=0}^{g} H_0(i)$.

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 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 Pixel darüber entspricht;
   - alle Ebenen mit beliebigem Schwellwert maximal grosse 4-Zusammenhangskomponenten $CC(g + 0.5)$ ergeben.

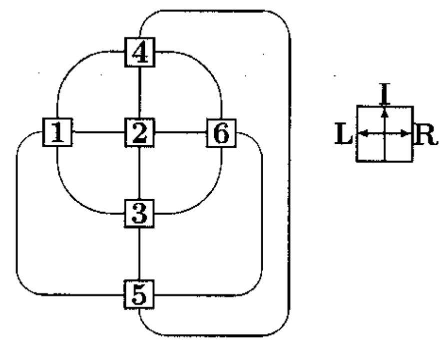


7. Bestimme die Anzahl der 4-Zusammenhangskomponenten $CC(t) = |\{Med_0(x, y) < t\}|$ für $t = 0.5, 1.5, \dots 6.5$ (in obiger Tabelle in Zeile $CC(g + 0.5)$ eintragen).

4 Minimale Pfade mit Würfeln (5)

Ein Würfel wird im linken unteren Eck eines 5 × 5 Bildrasters gelegt. Die oben aufscheinende Augenzahl wird in dem darunterliegende Pixel eingetragen. Durch Kippen des Würfels über eine seiner 4 Kanten kommt der Würfel auf dem jeweilig 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.

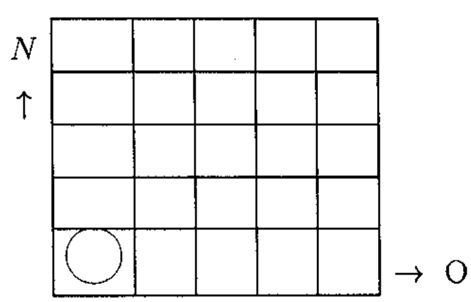
Die Struktur des Würfels ist durch seinen Aspectgraphen festgelegt, wobei nur die jeweils oben liegende Augenzahl sichtbar ist und ein einmaliges Kippen durch eine Kante ausgedrückt wird. Eine Folge von Kippbewegungen (z.B. 3,2,4,5,6,3) wird durch eine RULI-chain beschrieben: N 3: I^3RL. Entsprechende Bewegungen (L ...links, R...rechts, I...in dieselbe Richtung) erfolgen auch auf dem Pixelraster.



1. Platziere einen Würfel mit der Augenzahl $\operatorname{argmax}\{M_i | i = 2, 3, ...7\} - 1$ (bei Mehrdeutigkeiten die vordere Ziffer) im linken unteren Eck des 5×5 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 24 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. Jeder Pixel oberhalb und rechts des Startpixels hat in seinen Pfaden ein oder zwei Vorgänger!

3. Im Falle von zwei Vorgängern wird nur jener Pfad fortgesetzt, der im Pixel die geringere Augenzahl speichert.



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

Folge der Augenzahlen: ....

RLI-chain: ....

....

....

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Teil III: Selektion von Literatur (16)

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

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

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

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

5 Abstracts und Literaturausschnitte

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

B In computer vision there is a long history of work on shape representation and shape similarity. However, most of the existing methods have only a very limited possible application to distributed image databases, since the shape of objects must be restricted and known a priori. These methods are based on the close word assumption, which means that the application domain must be explicitly known, since prior knowledge of the application domain is necessary for parameter adjustment. Moreover, many of the existing approaches are very sensitive to noise. To systematize our discussion, we first suggest some necessary requirements for shape similarity measures that are used for retrieval of similar objects in distributed image databases.

C Lossless and lossy ... : It is desired to provide ... compression naturally in the course of progressive decoding. Examples of applications that can use this feature include medical images, where loss is not always tolerated; image archival applications, where the highest quality is vital for preservation but not necessary for display; network applications that supply devices with different capabilities and resources; and prepress imagery. It is also desired that the standard should have the property of creating embedded bit stream and allow progressive lossy to lossless buildup.

D The study on ... has gained increasing attention in recent years due to the active research in content-based image representation. For instance, the ability to locate image object such as a face can be exploited for image coding, editing, indexing or other user interactivity purposes. Moreover, face localization also provides a good stepping stone in facial expression studies. It is fair to say that the most popular approach to face localization is the use of color information, whereby estimating areas with skin color is often the first vital step of such strategy.

E ... is efficient in solving tree-like problems. Furthermore, the constructive steps of each ... can be different in the same iteration. It means that no requirements are demanded to estimate the total number of probable optimal solutions. This condition differs from other evolutionary computation methods like genetic algorithms. Some researchers have adopted ... to solve specific image processing or machine vision problems, like imitation and reproduction of human vision perception and optical illusions (Vallone and Merigot, 2003), texture classification (Zhuang and Mastorakis, 2005; Zheng et al., 2003), and edge detection (Zhuang and Mastorakis, 2005). In solving ..., each pixel of one image is assumed to be connected with its 8-neighborhood pixels. The distance between adjacent pixels is estimated from the original image, and the ... are placed on endpoints extracted from traditional ... detection approaches.

F The ... maps each image pixel into its smallest distance to regions of interest [Rosenfeld and Pfaltz 1966]. It is a fundamental geometrical operator with great applicability in computer vision and graphics, shape analysis, pattern recognition, and computational geometry. ... methods are useful propagation schemes that efficiently construct a solution to the eikonal differential equation [John 1982] in the integer lattice. This in turn, is related to many other important entities such as medial axes, Voronoi diagrams, shortest-path computation, and image segmentation. The ... can be defined in terms of arbitrary metrics. The Euclidean distance is often necessary in many applications, as it is the adequate model to numerous geometrical facts of the human-scale world. However, as in pure mathematics, some non-Euclidean metrics are much easier to manipulate and to compute.

G We propose EMD-L_1: a fast and exact algorithm for computing the ... (EMD) between a pair of histograms. The efficiency of the new algorithm enables its application to problems that were previously prohibitive due to high time complexities. The proposed EMD-L_1 significantly simplifies the original linear programming formulation of EMD. Exploiting the L_1 metric structure, the number of unknown variables in EMD-L_1 is reduced to $O(N)$ from $O(N^2)$ of the original EMD for a histogram with N bins. In addition, the number of constraints is reduced by half and the objective function of the linear program is simplified. Formally, without any approximation, we prove that the EMD-L_1 formulation is equivalent to the originalEMDwith a L1 ground distance. To perform the EMD-L_1 computation, we propose an efficient tree-based algorithm, Tree-EMD.

H The efficient and sequential EDT algorithms can be classified in terms of the order in which the pixels are processed. In the so-called ordered propagation algorithms, the smallest ... is computed starting from the seeds (0 distance) and progressively transmitting the information to other pixels in order of increasing distance. On the other hand, the raster scanning algorithms use 2D masks to guide the processing of pixels line by line, top to bottom, then bottom to top. Independent scanning schemes process each row of the image, independently of the other, and then process each column of the result. This process is similar to separable linear transforms, such as computing the Fourier transform of an image by a sequence of 1D transforms in orthogonal directions [Brigham 1988].

I ... is a technique for marking sharp intensity changes, and is important in further analyzing image content. However, traditional ... approaches always result in broken pieces, possibly the loss of some important .... This study presents an ant colony optimization based mechanism to compensate broken .... The proposed procedure adopts four moving policies to reduce the computation load. Remainders of pheromone as compensable ... are then acquired after finite iterations. Experimental results indicate that the proposed ... improvement approach is efficient on compensating broken ... and more efficient than the traditional ACO approach in computation reduction.

J ... is an important processing step in many image, video and computer vision applications. Extensive research has been done in creating many different approaches and algorithms for ... , but it is still difficult to assess whether one algorithm produces more accurate segmentations than another, whether it be for a particular image or set of images, or more generally, for a whole class of images. To date, the most common method for evaluating the effectiveness of a ... is subjective evaluation, in which a human visually compares the ... results for separate segmentation algorithms, which is a tedious process and inherently limits the depth of evaluation to a relatively small number of segmentation comparisons over a predetermined set of images.

K Previous studies have found that pixels belonging to skin region exhibit similar Cb and Cr values. Furthermore, it has been shown that skin color model based on Cb and Cr values can provide good coverage of all human races. This is based on the conjecture that the different skin color that viewers perceived from the image cannot be differentiated from the chrominance information of that image region. The apparent difference in skin color that viewers perceived is mainly due to the darkness or fairness of the skin. These features are characterized by the difference in the brightness of the color, which is governed by Y but not Cb and Cr.

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

M Simultaneously, ... emerged as a powerful and flexible graph matching paradigm that can be used to address different tasks in pattern recognition, machine learning, and data mining. The key advantages of ... are its high degree of flexibility, which makes it applicable to any type of graph, and the fact that one can integrate domain specific knowledge about object similarity by means of specific edit cost functions. Its computational complexity, however, is exponential in the number of nodes of the involved graphs. Consequently, exact ... is feasible for graphs of rather small size only. In the present paper we introduce a novel algorithm which allows us to approximately, or suboptimally, compute edit distance in a substantially faster way.

N The class of unsupervised objective evaluation methods is the only class of evaluation methods to offer ... algorithms the ability to perform self-tuning. Most ... are manually tuned; the parameters for the ... algorithm are determined during system development, prior to system deployment, based on the set of parameters that generate the best overall segmentation results over a predetermined set of test images. However, these parameters might not be appropriate for the segmentation of later images. It would be preferable to have a self-tunable segmentation method that could dynamically adjust the segmentation algorithms parameters in order to automatically determine the parameter options that generate better results. Pichel et al. [72] recently proposed one such system, which uses unsupervised evaluation methods to evaluate and merge sub-optimal segmentation results in order to generate the final segmentation.

O ... 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.

P The ... standard has been in use for almost a decade now. It has proved a valuable tool during all these years, but it cannot fulfill the advanced requirements of today. Todays digital imagery is extremely demanding, not only from the quality point of view, but also from the image size aspect. Current image size covers orders of magnitude, ranging from web logos of size of less than 100 Kbits to high quality scanned images of approximate size of 40 Gbits [20], [33], [43], [48]. The ... international standard represents advances in image compression technology where the image coding system is optimized not only for efficiency, but also for scalability and interoperability in network and mobile environments.

Q ... refers to the process of evaluating the structural similarity of graphs. A large number of methods for ... have been proposed in recent years [1]. The main advantage of a description of patterns by graphs instead of vectors is that graphs allow for a more powerful representation of structural relations. In the most general case, nodes and edges are labeled with arbitrary attributes. One of the most flexible methods for error-tolerant ... that is applicable to various kinds of graphs is based on the ... of graphs [2,3]. The idea of ... is to define the dissimilarity of graphs by the amount of distortion that is needed to transform one graph into another. Using the ... , an input graph to be classified can be analyzed by computing its dissimilarity to a number of training graphs. For classification, the resulting distance values may be fed, for instance, into a nearest-neighbor classifier.

R We empirically show that this new algorithm has an average time complexity of $O(N)$, which significantly improves the best reported supercubic complexity of the original EMD. The accuracy of the proposed methods is evaluated by experiments for two computation-intensive problems: shape recognition and interest point matching using multidimensional histogram-based local features. For shape recognition, EMD-L_1 is applied to compare shape contexts on the widely tested MPEG7 shape data set, as well as an articulated shape data set. For interest point matching, SIFT, shape context and spin image are tested on both synthetic and real image pairs with large geometrical deformation, illumination change, and heavy intensity noise.

S A similarity measure for silhouettes of 2D objects is presented, and its properties are analyzed with respect to retrieval of similar objects in image databases. To reduce influence of digitization noise as well as segmentation errors the shapes are simpli.ed by a new process of digital curve evolution. To compute our similarity measure, we first establish the best possible correspondence of visual parts (without explicitly computing the visual parts). Then the similarity between corresponding parts is computed and summed. Experimental results show that our shape matching procedure gives an intuitive shape correspondence and is stable with respect to noise distortions.

T 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.

6 Welche Ausschnitte gehören zu folgenden Titel ?

0 On Sampling Theorem, Wavelets, and Wavelet Transforms

Ausschnitt(e): ....

Begründung(en): ....

1 A bayesian approach to skin color classification in YCBCR color space

Ausschnitt(e): ....

Begründung(en): ....

2 Contrast enhancement using brightness preserving bi-histogram equalization

Ausschnitt(e): ....

Begründung(en): ....

3 An efficient earth movers distance algorithm for robust histogram comparison

Ausschnitt(e): ....

Begründung(en): ....

4 The JPEG 2000 Still Image Compression Standard

Ausschnitt(e): ....

Begründung(en): ....

5 Image segmentation evaluation: A survey of unsupervised methods

Ausschnitt(e): ....

Begründung(en): ....

6 Edge detection improvement by ant colony optimization

Ausschnitt(e): ....

Begründung(en): ....

7 2D Euclidean Distance Transform Algorithms: A Comparative Survey

Ausschnitt(e): ....

Begründung(en): ....

8 Approximate graph edit distance computation by means of bipartite graph matching

Ausschnitt(e): ....

Begründung(en): ....

9 Application of planar shape comparison to object retrieval in image databases

Ausschnitt(e): ....

Begründung(en): ....