

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

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.

Y = fft2(X)

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

Y = fftshift(X)

rearranges the outputs of fft, fft2, and fftn by moving the zero-frequency component to the center of the array.

h = fspecial('gaussian',hsize,sigma)

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

BW = im2bw(I,level)

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

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

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.

J = imnoise(I,'salt & pepper',d)

adds salt and pepper noise to the image I, where d is the noise density.

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',[20 20],10);

Begründung:

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

Begründung:

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

Begründung:

4. = 1-im2bw(,200/255);

Begründung:

5. = imhist(M);

Begründung:

6. = imdilate(,strel('disk',15));

Begründung:

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

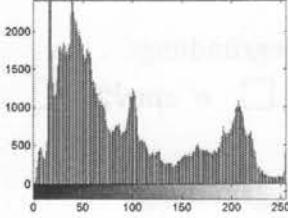
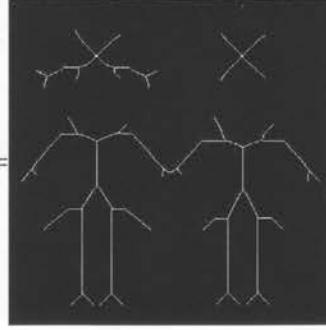
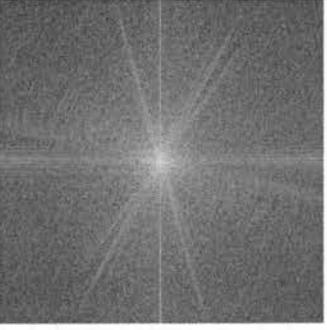
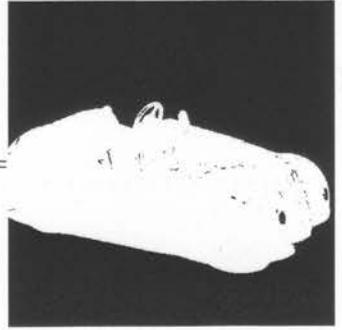
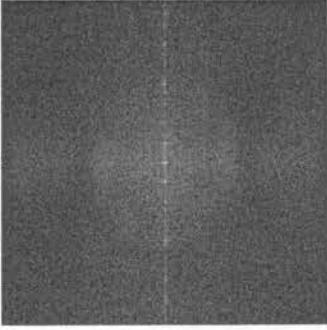
Begründung:

8. = bwdist(~);

Begründung:

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

Begründung:

Binärbilder		Grauwertbilder			
A=		B=		C=	
D=		E=		F=	 <p>A histogram showing the distribution of pixel intensities. The x-axis represents the grayscale value from 0 to 255, and the y-axis represents the frequency from 0 to 2000. The distribution is highly skewed, with a major peak at approximately 20 pixels and several smaller peaks at higher values.</p>
G=		H=		I=	
J=		K=		L=	

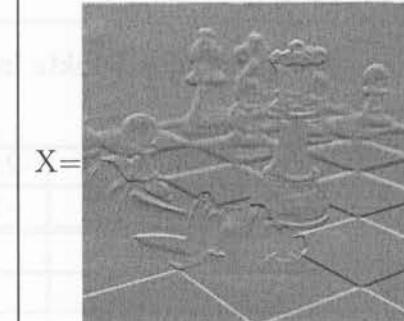
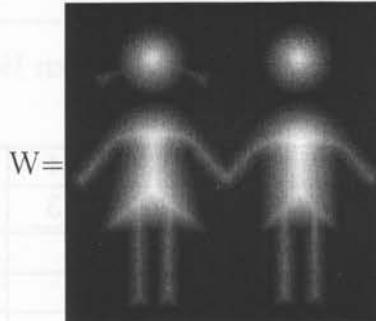
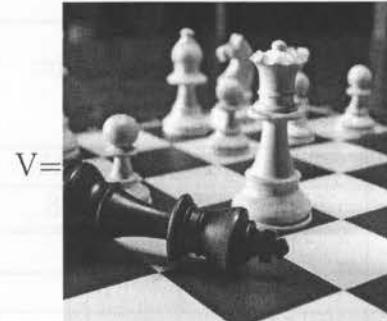
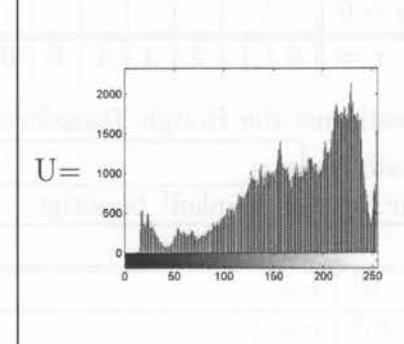
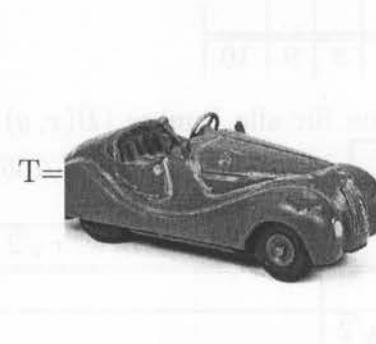
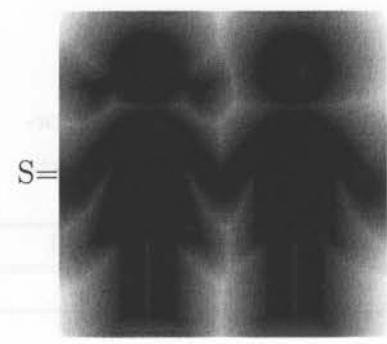
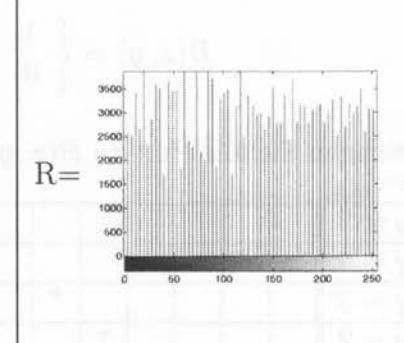
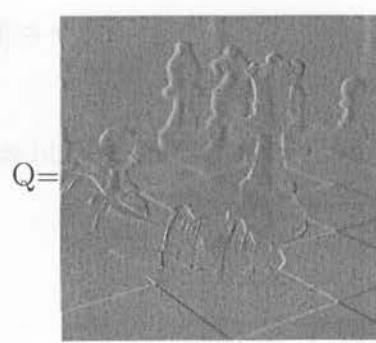
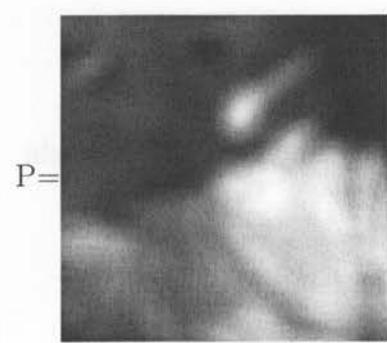
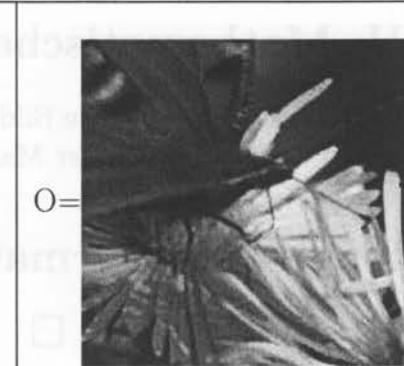
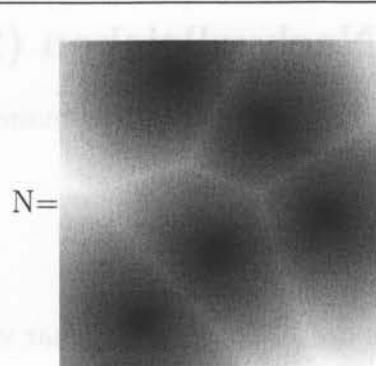
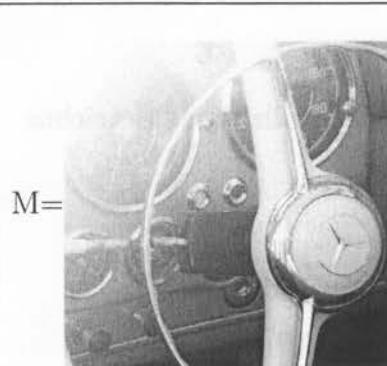
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Grauwertbilder

0

255



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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)

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

$$B(x, y) = \begin{cases} 1 & \text{wenn } \text{mod}(x - 2, S) = 0, x \in [0, 10], y \in [0, 5] \\ 0 & \text{sonst} \end{cases}$$

- 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

- Bestimme die Hough-Transformation für alle Punkte ($B(x, y) = 1$) mit der Hesse'schen Normalform $r = \square$ und $\theta \in \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$. Zuerst werden die r -Werte für die vier Winkel¹ benötigt:

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

- Trage die Anzahl der Punkte in den folgenden quantisierten Hough-Akkumulator $H(\theta, r)$ ein:

$r \in$...-5,-6	-4	-3	-2,-1	0	1,2	3	4	5,6	7	8,9	10	11...
$r\sqrt{2} \in$...-4	-3	-2	-1	0	1	2	3	4	5	6	7	8...
$\theta = 0^\circ$													
$\theta = 45^\circ$													
$\theta = 90^\circ$													
$\theta = 135^\circ$													

¹ $\cos 45^\circ = \sin 45^\circ = \sin 135^\circ = 1/\sqrt{2}$

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2 Morphologische Transformation zu Punktraster (5)

1. Sei $S = \text{mod}(M, 3) + 3 = \square$ der Abstand zwischen den Linien eines Rasters.

2. Das Raster sei wie folgt definiert:

$$R(x, y) = \begin{cases} 1 & \text{wenn } \text{mod}(x - 2, S) = 0 \text{ oder } \text{mod}(y - 2, S) = 0 \\ 0 & \text{sonst} \end{cases}$$

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

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

Strukturelemente

		D	
	C		
E			
			F

4. Dieses Binärbild B soll in ein Punktgitter P umgewandelt werden, das nur die Kreuzungspunkte 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. $Z_1 = \dots$

2. $Z_2 = \dots$

3. $P = \dots$

7. Wieviele Punkte enthält $|P| = \square$?

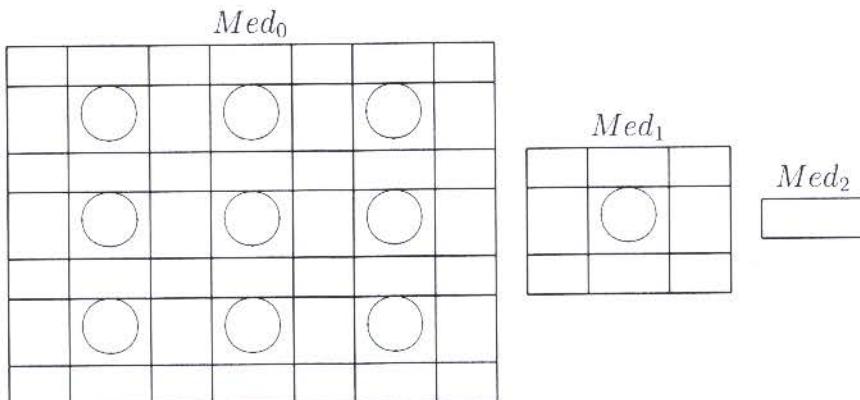
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3 Medianpyramide (5 P)

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
$H_1(g) =$								

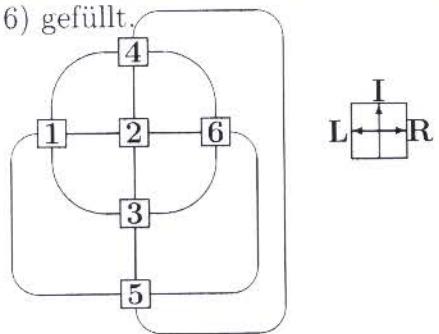
2. Zur Bestimmung des Median dient das kumulative Histogramm $K_0(g) = \sum_{i=0}^g H_0(i)$.
3. Das zentrale Element von Med_0, Med_1, Med_2 wird mit dem Median aller 49 Pixel der Grundebene Med_0 gefüllt.
4. Das Histogramm der Ebene 1 der $3 \times 3/4$ Medianpyramide wird durch $H_1(g) \approx [H_0(g)/5]$ 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 wohlgeformt sind.



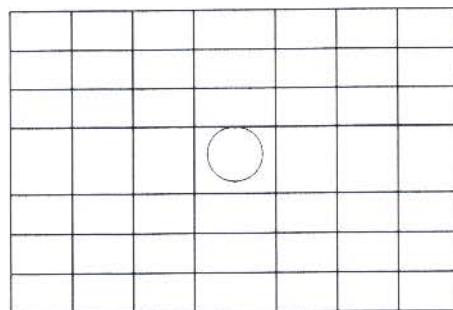
7. Begründungen:
-
-

4 Minimale Pfade mit Würfeln (5)

Ein Würfel wird ins Zentrum eines 7×7 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 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 wird durch eine RULI-chain beschrieben: $3, 2 : I \rightarrow 4 : I \rightarrow 5 : R \rightarrow 6 : L \rightarrow 3$. Entsprechende Bewegungen (L...links, R...rechts, I...in dieselbe Richtung) erfolgen auch auf dem Pixelraster.



1. Platziere einen Würfel mit der Augenzahl $\text{argmax}\{M_i | i = 2, 3, \dots, 7\} - 1$ (bei Mehrdeutigkeiten die vordere Ziffer) im Zentrum des 7×7 Feldes und trage die Augenzahl im markierten Zentrum ein. Von hier starten Pfade in vier Richtungen N,O,S,W.
2. Sie haben die Aufgabe, jede der 48 restlichen Positionen durch schrittweises Kippen des Würfels und Eintragen der oben liegenden Augenzahl zu füllen. Alle Pfade beginnen im Zentrum und führen jeweils zu Pixeln, die vom Zentrum weiter 4-entfernt sind. Jeder Pixel ausserhalb des Zentrums 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. Welche Eigenschaften hat das resultierende 7×7 Feld?

.....

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Notizen

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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 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 To achieve this, we learn a non-linear transformation model by minimizing a novel margin-based cost function, which aims to separate matching descriptors from two classes of non-matching descriptors. Training data is generated automatically by leveraging geometric consistency. Scalable, stochastic gradient methods are used for the optimization. For the case of particular object retrieval, we demonstrate impressive gains in performance on a ground truth dataset: our learnt 32-D descriptor without spatial re-ranking outperforms a baseline method using 128-D SIFT descriptors with spatial re-ranking.
- B 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. Digital imaging has become an integral part of the Internet, and ... is a powerful new tool that provides power capabilities for designers and users of networked image applications [41].

- 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 . . . is a common technique for image segmentation. However, its use for automatic medical image segmentation has been limited particularly due to oversegmentation and sensitivity to noise. Employing prior shape knowledge has demonstrated robust improvements to medical image segmentation algorithms. We propose a novel method for enhancing . . . segmentation by utilizing prior shape and appearance knowledge. Our method iteratively aligns a shape histogram with the result of an improved k-means clustering algorithm of the . . . segments. Quantitative validation of magnetic resonance imaging segmentation results supports the robust nature of our method.
- E The extraction of convex hull can be a single process which finds significant convex deficiencies along the boundary. The shape can then be represented by a string of concavities. A fuller representation of the shape may be obtained by a recursive process which results in a concavity tree. Here the convex hull of an object is first obtained with its convex deficiencies, then the convex hulls and deficiencies of the convex deficiencies are found, then the convex hulls and deficiencies of these convex deficiencies, and so on until all the derived convex deficiencies are convex.
- 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 . . . has increasingly been recognized as a powerful segmentation process due to its many advantages [4], including simplicity, speed and complete division of the image. Even with target regions having low contrast and weak boundaries, . . . can always provide closed contours. In addition, . . . typically occur at the most obvious contours of the object, even when oversegmentation is severe. This positioning of contours can offer a stable and accurate initialization for other post-processing and segmentation techniques.
- H 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).

- 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 We propose a novel method of exploiting inter-view correlation among cameras that have overlapping views in order to deliver error-resilient video in a distributed multi-camera system. The main focus in this work is on robustness which is imminently needed in a wireless setting. Our system has low encoding complexity, is robust while satisfying tight latency constraints, and requires no inter-sensor communication. In this work, we build on and generalize PRISM, an earlier proposed single-camera distributed ... system. Specifically, decoder motion search, a key attribute of single-camera PRISM, is extended to the multi-view setting to include decoder disparity search based on two-view camera geometry. Our proposed system, dubbed PRISM-MC (PRISM multi-camera), achieved PSNR gains of up to 1.7 dB over a PRISM based simulcast solution in experiments over a wireless channel simulator.
- K A new ... criterion is formulated for segmenting small objects by exploring the knowledge about intensity contrast. It is the weighted sum of within-class variance and intensity contrast between the object and background. Theoretical bounds of the weight are given for the uniformly distributed background and object, followed by the procedure to estimate the weight from prior knowledge. Tests against two real and two synthetic images show that small objects can be extracted successfully irrespective of the complexity of background and difference in class sizes.
- L However, we have to be careful in taking care of the dependencies in decoding. For example, in the setup illustrated in Figure 4, when decoding the video from camera 1, we would need to make use of the current frame of camera 2 for decoder disparity search, and vice versa. Our solution is to first decode all the views using decoder motion search. For each block that is not successfully decoded, decoder disparity search is performed on the currently available available reconstructions (possibly with error concealment). As it is possible that a successful disparity decoding in one view can lead to a successful decoding in another view, we will attempt decoder disparity search across all cameras until either all blocks are successfully reconstructed or there are no further successful reconstructions.
- M 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.

- N Whilst being ostensibly similar to textual words, visual words as generated through clustering from a lot more noise and dropout compared to text. This is caused partly by errors and failures in interest point detection and description, but also by quantization descriptors that lie close to a Voronoi boundary after clustering being assigned to the wrong visual word. Previous work attempted to overcome quantization errors by compensating for mis-clustered descriptors using additional information in the retrieval index, for example by soft-assigning descriptors [,7], or by performing more work at query time [1,8].
- O This paper introduces three new vertex chain codes. Firstly, considering that the vertex chain code uses 2 bits to represent only three code elements, a new code is introduced without increasing the average bits per code. The second case introduces a variable-length vertex chain code. Finally, a new compressed chain code is proposed based on the Huffman method. The continuation introduces a method for quantificationally evaluating the efficiency of chain codes. The efficiencies of the new vertex chain codes are then compared theoretically and practically against the most popular chain codes. The result of the comparison shows that the new compressed chain code is the most efficient.
- P Typically, the geometric similarity between two shapes is a measure of how well the primitives forming the shapes and / or their spatial organizations agree [919]. Tree data structure has been widely used for describing shapes, as it provides a natural representation of the inclusion relations of the primitives. When a shape (primitives and their inclusion relations) is represented by a tree, the best correspondence between two given shapes can be expressed as the best partial match between their trees. Accordingly, the shape dissimilarity is computed as the edit distance which is defined as the cost of transforming the first tree into the second one by using node removal, node insertion and attribute change operations [20]. In the shape literature, it is an accepted practice to form tree or graph descriptions using shape skeletons, and to match these descriptions using edit distance [12,13,15,16,21]. Typically, these works are generic and they ignore contextual effects, despite the observation that human dissimilarity judgements are biased by the other shapes [5,6,8,22,23,24].
- Q The global characteristics of the ridge pattern may be described by the orientation image and the frequency image (see Section 3.1). Unfortunately, local frequency information is not among the mandatory data required by the ISO template; in case the template contains ridge count information in the Extended Data, an effective technique may be based on the interpolation of the ridge count values between different pairs of minutiae; however, such an additional investigation is outside the aims of this work. On the other hand, reconstructing a frequency image from the minutiae information seems to be almost impracticable: under some simplifying hypothesis, one may try to infer something from the relative position of minutiae pairs and the singularity positions, but usually, the number of minutiae is too low to come to any robust conclusion.
- R The Otsu method [10] uses within-class variance for image segmentation and works well when the object and background are distinct in intensity and of similar sizes. The difference in sizes between the object and background plays a more important role than the intensity contrast in the Otsu method.

S Skeletal trees are commonly used in order to express geometric properties of the shape. Accordingly, tree-edit distance is used to compute a dissimilarity between two given shapes. We present a new tree-edit based shape matching method which uses a recent coarse skeleton representation. The coarse skeleton representation allows us to represent both shapes and shape categories in the form of depth-1 trees. Consequently, we can easily integrate the influence of the categories in to shape dissimilarity measurements. The new dissimilarity measure gives a better within group versus between group separation, and it mimics the asymmetric nature of human similarity judgements.

T The main reason for the popularity of ... is its memory compactness. ... can be viewed as a connected sequence of straight-line segments with specified lengths and directions. The first ... for representing digital curves was introduced by Freeman [6] in 1961 and his code remains the most widely used coding technique. Freeman's code describes the movement along a digital curve or a sequence of border pixels by using so-called 8-connectivity. The direction of each movement is encoded by the numbering scheme $i|i = 0, 1, 2, \dots, 7$ denoting a counter-clockwise angle of $45^\circ \times i$ regarding the positive x-axis, ...

6 Welche Ausschnitte gehören zu folgenden Titel ?

- 0 Robust distributed multi-view video compression for wireless camera networks
Ausschnitt(e):
Begründung(en):
- 1 Watershed segmentation using prior shape and appearance knowledge
Ausschnitt(e):
Begründung(en):
- 2 Compressed vertex chain codes
Ausschnitt(e):
Begründung(en):
- 3 Thresholding based on variance and intensity contrast
Ausschnitt(e):
Begründung(en):
- 4 Descriptor Learning for Efficient Retrieval
Ausschnitt(e):
Begründung(en):
- 5 Review of shape representation and description techniques
Ausschnitt(e):
Begründung(en):
- 6 Dissimilarity between two skeletal trees in a context
Ausschnitt(e):
Begründung(en):
- 7 A Syntactic Approach to Scale-Space-Based Corner Description
Ausschnitt(e):
Begründung(en):
- 8 Fingerprint Image Reconstruction from Standard Templates
Ausschnitt(e):
Begründung(en):
- 9 The JPEG 2000 Still Image Compression Standard
Ausschnitt(e):
Begründung(en):