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

Schriftliche Prüfung aus Grundlagen der Digitalen Bildverarbeitung WS 2009/2010

Walter G. Kropatsch

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

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Diese Prüfung besteht aus drei Teilen auf die Sie insgesamt 50 Punkte erreichen können. Für besonders gute Begründungen können Zusatzpunkte erreicht werden. Die Dauer der Prüfung beträgt 90 Minuten. Es gilt der folgende Notenschlüssel:

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

Teil I: Interpretation von Bildoperationen (14)

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

Matlab Referenz

Allgemeines

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

Notationen

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

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

Command Reference

`Y = abs(X)`
returns an array Y such that each element of Y is the absolute value of the corresponding element of X.

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

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

`BW = edge(I,'canny',thresh,sigma)`
specifies sensitivity thresholds for the Canny method. thresh is a two-element vector in which the first element is the low threshold, and the second element is the high threshold. sigma is the standard deviation of the Gaussian filter.

`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.

`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:

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

`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.

`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 letzten vier verschiedenen Ziffern Ihrer Matrikelnummer entsprechen (sollten nur 3 verschiedene Ziffern auftreten, so wird durch "4" ergänzt), gibt es einen Punkt zusätzlich für eine korrekte Antwort, einen Abzugspunkt für eine falsche Antwort. Für entsprechend gute und korrekte Begründungen kann es Zusatzpunkte geben, die Verluste in anderen Abschnitten ausgleichen können!

0. ☐ `= im2bw(` ☐ `,200/255);`

   Begründung: ....

1. ☐ `= 1-im2bw(` ☐ `,100/255);`

   Begründung: ....

2. ☐ `= imerode(` ☐ `,strel('disk',11));`

   Begründung: ....

3. ☐ `= log1p(abs(fftshift(fft2(L))));`

   Begründung: ....

4. ☐ `= "Hough-Transform"(N);`

   Begründung: ....

5. ☐ `= log1p(abs(fftshift(fft2(K))));`

   Begründung: ....

6. ☐ `= bwmorph(` ☐ `,'skel',Inf);`

   Begründung: ....

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

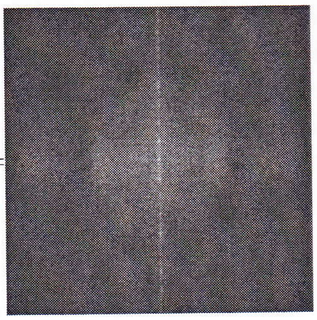
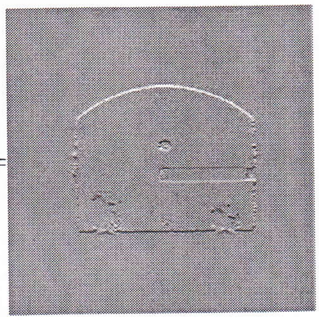
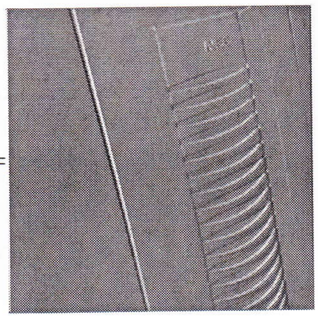
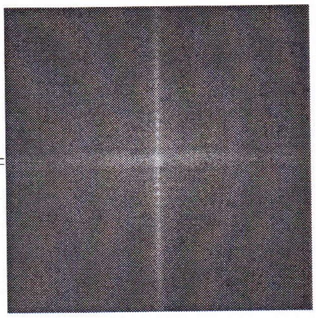
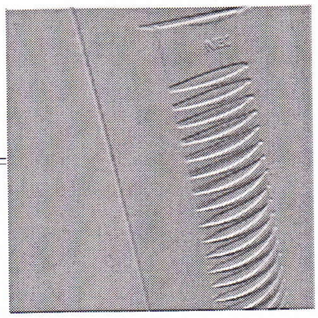
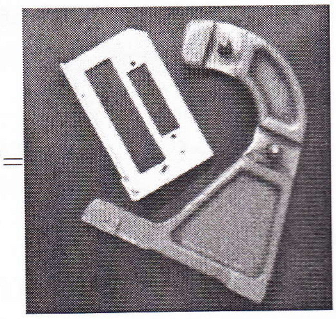
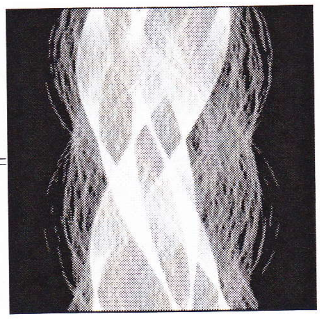
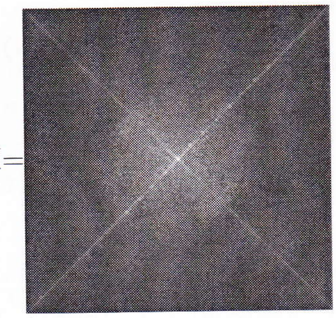
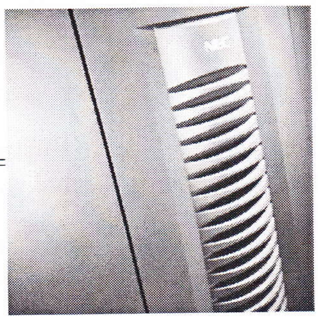
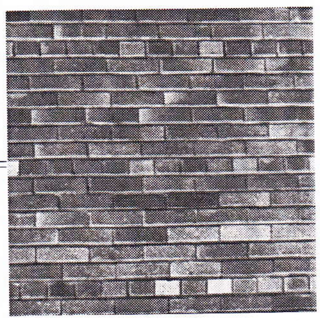
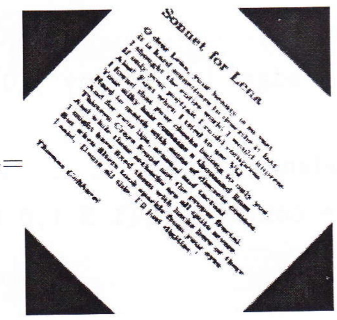
   Begründung: ....

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

   Begründung: ....

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

   Begründung: ....

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

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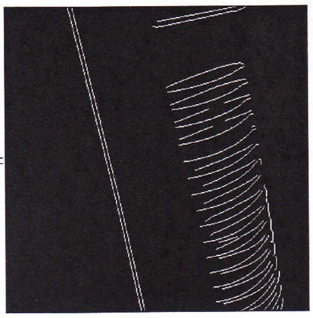
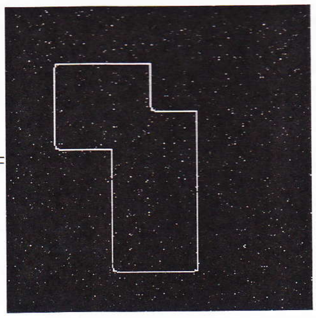
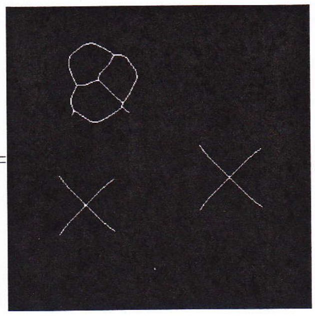
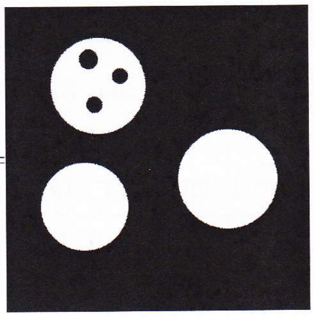
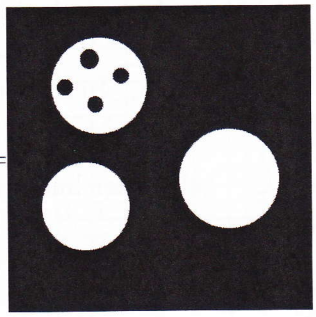
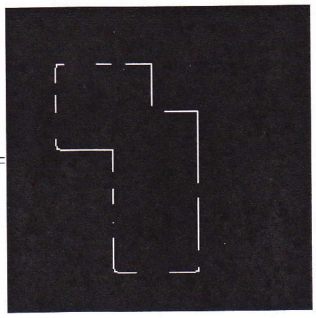
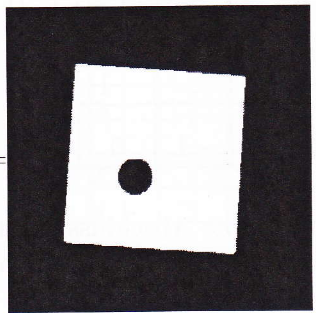
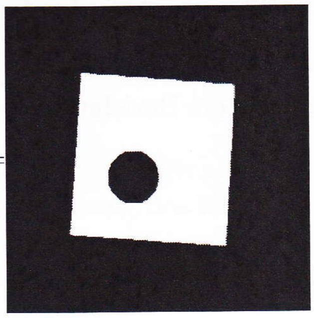
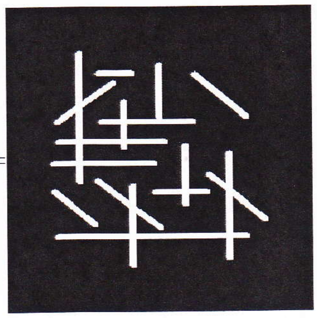
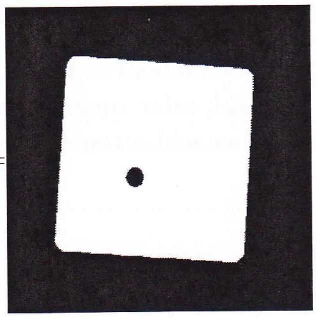
Binärbilder		
M= 	N= 	O= 
P= 	Q= 	R= 
S= 	T= 	U= 
V= 	W= 	X= 

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Teil II: Mathematisches Nachvollziehen (20)

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

1 Rekonstruktion aus Kantenbildern (5)

1. Ein 4×4 Grauwertbild I wurde mit einem horizontalen und einem vertikalen Kantenfilter gefaltet: $H = (-1 \quad 1) * I$, $V = \begin{pmatrix} 1 \\ -1 \end{pmatrix} * I$. Für die Ränder wurde in beiden Fällen der zyklische Abschluß angenommen. Rekonstruieren Sie aus den 16 bekannten Werten alle restlichen 32 Werte von H, V, I.

2. In die mit $\bigcirc$ gekennzeichneten Pixel tragen Sie die 7 Ziffern Ihrer Matrikelnummer ein (beliebig):

$$H = \left(\begin{array}{|c|c|c|c|} \hline 1 & 0 & -1 & \\ \hline 0 & -1 & \bigcirc & \\ \hline -1 & \bigcirc & -1 & \\ \hline \bigcirc & -1 & 0 & \\ \hline \end{array}\right), \quad V = \left(\begin{array}{|c|c|c|c|} \hline \bigcirc & & & \\ \hline \bigcirc & & & \\ \hline \bigcirc & & & \\ \hline & & & \\ \hline \end{array}\right), \quad I = \left(\begin{array}{|c|c|c|c|} \hline & & & \\ \hline & & & \\ \hline & & \bigcirc & \\ \hline & & & \\ \hline \end{array}\right).$$

3. Tip: Der zyklische Abschluss stellt eine Beziehung zwischen den vier Werten der Zeilen von H und der Spalten von V her. Welche?

   ....

   ....

4. Tip: diagonal benachbarte Pixel von I sind über zwei 4-Wege verbunden: zuerst horizontal und dann vertikal; oder zuerst vertikal und dann horizontal. Das ergibt eine weitere Beziehung zwischen zwei benachbarten Werten von H und von V:

   ....

   ....

5. Welche Formeln werden für die Rekonstruktion von I verwendet?

   ....

   ....

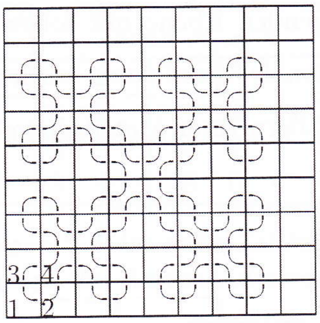
2 RULI Chaincode Grammatik (5)

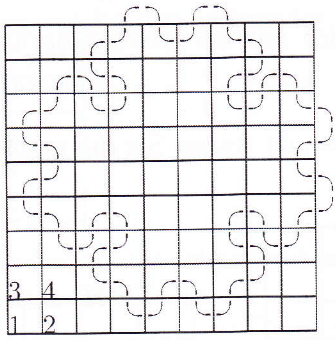
1. Die folgenden zwei Grammatiken $G = (\{R_n, L_n\}, \{S, R_i, L_i | 0 \leq i < n\}, S, P)$ erzeugen je eine Klasse von RULI Chain Codes (CC) nach einer vorgegebenen Anzahl von Substitutionen n.

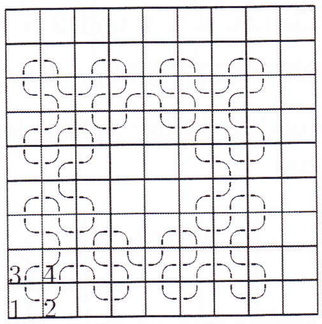
   $P: \quad S \rightarrow R_0R_0R_0R_0;$

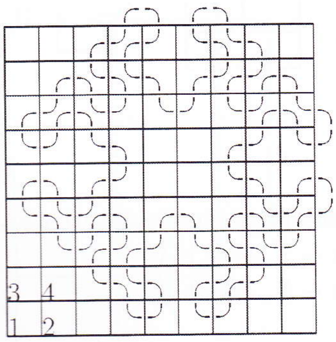
Wenn $M_3 < 5$	Wenn $M_3 \geq 5$
$R_{i-1} \rightarrow L_iR_iR_i, 1 \leq i < n;$	$R_{i-1} \rightarrow L_iR_iR_iR_iR_iL_i, 1 \leq i < n;$
$L_{i-1} \rightarrow L_i, 1 \leq i < n;$	$L_{i-1} \rightarrow L_iR_iL_i, 1 \leq i < n$

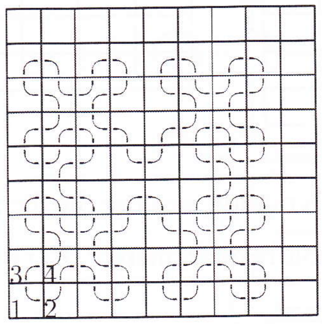
2. Welche der folgenden Figuren wird von Ihrer Grammatik erkannt?

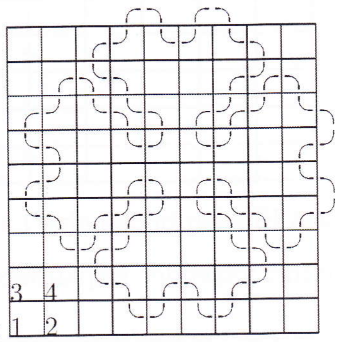
A: 

B: 

C: 

D: 

E: 

F: 

$M_3 =?$	Figur	$n =?$

3. Welche Folge von RULI-CC wird von der gewählten Grammatik erzeugt (formale Sprache, z.B. $((RL)^nRR)^2$)?

   ....

4. Ableitung des RULI-Chain Codes der gewählten Figur

   ....

   ....

   ....

3 Rekonstruktion aus Laplacepyramide (5 P)

1. Die Grundebene einer $2 \times 2/4$ Laplacepyramide wird aus einer der Figuren A,B,C,D,E,F des Beispiels 2 bestimmt, wobei der linke untere Pixel $(0,0)$ des 8×8 Bildes in der Figur als 1,2,3 oder 4 gekennzeichnet ist:

$M_7 =$	0	1	2	3	4	5	6	7	8	9
Fig.	A	B	C	D	E	F	A	C	D	E
$(0,0)$	2	1	2	1	2	1	4	4	2	4

2. Die 8×8 Werte der Grundebene ergeben sich aus der Anzahl der RULI-codes des korrespondierenden Pixels der Figur (0,1, oder 2).

3. Die Ebenen 4×4 und 2×2 werden aus der jeweilig darunter liegenden Ebene mit folgender Reduktionsfunktion bestimmt: $R\begin{pmatrix} a & b \\ c & d \end{pmatrix} = \left\lfloor \frac{a+b+c+d}{3} \right\rfloor$. Rationale Quotienten werden abgerundet. In der Spitze der Pyramide tragen Sie die größte der Ziffern Ihrer Matrikelnummer ein.

,

,

,

4. Diese 4 Ebenen bilden eine Laplace Pyramide, aus der Sie die zugrundeliegende Grauwertpyramide mit folgender Expansionsfunktion rekonstruieren: $E(x) = \begin{pmatrix} x-1 & x-1 \\ x-1 & x-1 \end{pmatrix}$.

,

,

,

Begründung: ....

....

....

....

....

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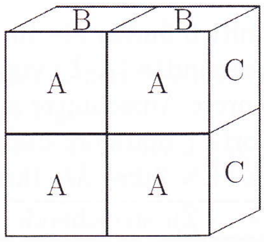
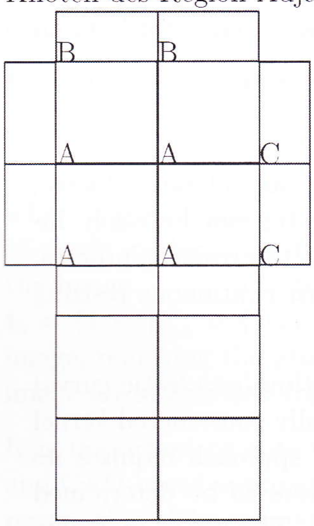
4 Vier Würfel (5)

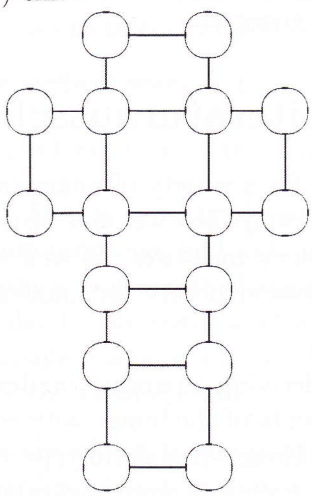


1. Vier Würfel werden wie folgt zusammengelegt:
   Die 6 Würfelflächen tragen die Zahlen 1 bis 6, wobei gegenüberliegende Zahlen sich zu 7 ergänzen. Die drei sichtbaren Zahlen A, B, C bestimmen sich aus folgender Tabelle

	Wenn $M_i = 4$							$\forall_i M_i \neq 4$
$i =$	1	2	3	4	5	6	7	8
A	1	1	1	1	2	2	3	4
B	2	2	3	4	3	4	5	5
C	3	4	5	5	6	6	6	6

2. Tragen Sie die sechs Zahlen in die Flächen der folgende Abwicklung der vier Würfel und die Knoten des Region Adjacency Graphen (RAG) ein.





3. Ergänzen Sie die fehlenden Kanten (ohne Kreuzungen!) im RAG.
   Der RAG hat ☐ Knoten und ☐ Kanten.

4. Zeichnen Sie den dualen Graphen über den RAG.
   Der duale Graph hat ☐ Knoten und ☐ Kanten.

5. Die Knoten des dualen Graphen sind von Zyklen des RAG umgeben. Wieviele dieser Zyklen tragen 3 verschiedene Zahlen? ☐

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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 LETZTEN Ziffer M_7 Ihrer Matrikelnummer streichen Sie 8 Literaturausschnitte weg:

M_7	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** (bitte in Abschnitt 1 markieren) 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 This operator can be used for a variety of image manipulations including: aspect ratio change, image retargeting, content amplification and object removal. The operator can be easily integrated with various saliency measures, as well as user input, to guide the resizing process. In addition, we define a data structure for multi-size images that support continuous resizing ability in real time.

B We present a method for deriving a parametric description of a conic section (quadratic curve) in an image from the moments of the image with respect to several specially constructed kernel functions. In contrast to Hough-transform-type methods, the moment approach requires no large accumulator array. Judicious implementation allows the parameters to be determined using five multiplication operations and six addition operations per pixel. The use of moments renders the calculation robust in the presence of high-frequency noise or texture and resistant to small-scale irregularities in the edge. Our method is generalizable to more complex classes of curves with more parameters and to surfaces in higher dimensions.

C An orientability measure determines how orientable a shape is; i.e. how reliable an estimate of its orientation is likely to be. This is valuable since many methods for computing orientation fail for certain shapes. In this paper several existing orientability measures are discussed and several new orientability measures are introduced. The measures are compared and tested on synthetic and real data.

D Image parts of known shapes can also be detected by "template matching". Matching methods are also studied in image processing; but many such methods, particularly those involving inexact matching, were developed in an image analysis context [7, ...210], to handle objects whose appearances can vary.

E A shape similarity measure useful for shape-based retrieval in image databases should be in accord with our visual perception. This basic property leads to the following requirements:
(1) A shape similarity measure should permit recognition of perceptually similar objects that are not mathematically identical.
(2) It should not be effected by distortions (e.g., digitization noise and segmentation errors).
(3) It should preserve significant visual parts of objects.
(4) It should not depend on scale, orientation, and position of objects.
If we want to apply a shape similarity measure to distributed image databases, where the object classes are generally unknown a priori (e.g., in the Internet), it is necessary that:
(5) A shape similarity measure is universal, in the sense that it allows us to identify or distinguish objects of arbitrary shapes, i.e., no restrictions on shapes are assumed.

F Haralicks coefficients are usually calculated from the average co-occurrence matrix obtained by averaging the matrices calculated for 0°, 45°, 90°, and 135° directions. The matrices are computed for one or several, experimentally selected, distance parameter values. In most of the cases, Haralicks coefficients utilized are calculated for only one distance parameter value. In this work, we propose a different ways of exploiting the information contained in Haralicks coefficients computed using several distance parameter d_i values. Rather than carefully selecting an appropriate distance parameter value, the information gathered in the co-occurrence matrices computed for several distance parameter values is efficiently utilized.

G Formally, let $\mathbf{I}$ be an $n \times m$ image and define a vertical seam to be:

$$s^x = \{s_i^x\}_{i=1}^n = \{(x(i), i)\}_{i=1}^n, s.t.\forall i, |x(i) - x(i-1)| \leq 1$$

where x is a mapping $x : [1, \ldots, n] \mapsto [1, \ldots, m]$ That is, a vertical seam is an 8-connected path of pixels in the image from top to bottom, containing one, and only one, pixel in each row of the image. ... The pixels of the path of seam s (e.g. vertical seam $\{s_i\}$) will therefore be $\mathbf{I}_s = \{\mathbf{I}(s_i)\}_{i=1}^n = \{\mathbf{I}(x(i), i)\}_{i=1}^n$. Note that similar to the removal of a row or column from an image, removing the pixels of a seam from an image has only a local effect: all the pixels of the image are shifted left (or up) to compensate for the missing path.

H It is important to note that in bringing the model closer to the image, the appearance-based and CAD-based approaches have altered the problem definition from generic to exemplar object recognition. The systems developed in the 70s cannot be compared to those developed today, for their target domains are different. We must acknowledge the efficacy of appearance-based recognition systems for exemplar recognition; provided that the above limitations can be overcome, this technique may emerge as the best method for recognizing exemplars. However, it is important to acknowledge that the prototypical recognition problem is an important one and, despite the vision communitys movement toward appearance-based methods, the hypothesis that these (or their analogous 3D template-based) methods can scale up to perform prototypical object recognition is dubious. What, then, has led us away from the important problem of generic object recognition?

I Effective resizing of images should not only use geometric constraints, but consider the image content as well. We present a simple image operator ... that supports content-aware image resizing for both reduction and expansion. A seam is an optimal 8-connected path of pixels on a single image from top to bottom, or left to right, where optimality is defined by an image energy function. By repeatedly carving out or inserting seams in one direction we can change the aspect ratio of an image. By applying these operators in both directions we can retarget the image to a new size. The selection and order of seams protect the content of the image, as defined by the energy function.

J When comparing shapes in image databases we have to deal not only with distortions caused by noise but also with the change of object view due to change of perspective and due to motion, e.g., bending of object parts or change of a relative position among parts. In this section, we present experimental results that illustrate that our shape similarity measure is robust with respect to all these distortions. This means that even a substantial amount of these distortions will result in small changes of the similarity values. All figures corresponding to the experiments of shape comparison show abstracted shapes of original input images at an automatically derived stage of abstraction. Observe that although the abstracted versions are used to find the part correspondence and to compute the similarity values, it is no problem to backtrace the corresponding parts to the original shapes. In all .gures the corresponding visual parts obtained in the course of computation of our similarity measure are indexed with the same numbers in the counter-clockwise direction. For visual convenience the parts are drawn slightly displaced.

K Upon entering a room, one first notices the presence of a particular object, such as a dog, before realizing it is either a Siberian Husky or that it is Loki, a particular Siberian. This example, modified from important studies by Rosch et al. (1976), suggests that there is an organization to our object memory, and that this organization facilitates recognition. Initially, particular instances are not recognized; rather, objects are first categorized at a basic level of abstraction (Rosch et al., 1976). The object is recognized as belonging to the categorydogbefore more detailed, or subordinate levels, are refined. This motivating example is at the heart of this paper: we seek a technique for object recognition based on such entry-level, generic descriptions. We interpret entry-level to mean generic in a technical sense, and then proceed to develop a formal system for matching based on it.

L **Elongation** Consider the covariance matrix constructed from the second order central moments of the shape

$$C = \begin{vmatrix} \mu_{20} & \mu_{11} \\ \mu_{11} & \mu_{02} \end{vmatrix}. \tag{1}$$

The eigenvalues of C denoted by I_1 and I_2 provide the variances of the shape along the major and minor principal axes. and can be used to form a measure of elongation [5], which in turn is an indication of ...

M Nonetheless, the fact that the approach was proposed more than 30 years ago, the coefficients still remain amongst the most popular and the most discriminative types of texture features [8].

N 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.

O The recognition community has typically avoided bridging the representational gap between traditional, low-level image features and generic models. Instead, the gap has been artificially eliminated by either bringing the image closer to the models using simple scenes containing idealized, textureless objects or by bringing the models closer to the images using 3D CAD model templates or 2D appearance model templates. In this paper, we attempt to bridge the representational gap for the domain of model acquisition. Specifically, we address the problem of automatically acquiring a generic 2D view-based class model from a set of images, each containing an exemplar object belonging to that class. We introduce a novel graph-theoretical formulation of the problem in which we search for the lowest common abstraction among a set of lattices, each representing the space of all possible region groupings in a region adjacency graph representation of an input image. The problem is intractable and we present a shortest path-based approximation algorithm to yield an efficient solution. We demonstrate the approach on real imagery.

P 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. Then, we briefly review some of the existing approaches from the perspective of these requirements.

Q For gray-scale images with information that is inherently binary such as text or graphics, binarization is usually performed first. The objective of binarization is to automatically choose a threshold that separates the foreground and background information. Selection of a good threshold is often a trial and error process (see figure 3). This becomes particularly difficult in cases where the contrast between text pixels and background is low (for example, text printed on a gray background), when text strokes are very thin resulting in background bleeding into text pixels during digitization, or when the page is not uniformly illuminated during data capture. Many methods have been developed for addressing these problems including those that model the background and foreground pixels as samples drawn from statistical distributions and methods based on spatially varying (adaptive) thresholds. Whether global or adaptive thresholding methods are used for binarization, one can seldom expect perfect results.

R We have been developing a theory for the generic representation of 2-D shape, where structural descriptions are derived from the shocks (singularities) of a curve evolution process, acting on bounding contours. We now apply the theory to the problem of shape matching. The shocks are organized into a directed, acyclic shock graph, and complexity is managed by attending to the most significant (central) shape components first. The space of all such graphs is highly structured and can be characterized by the rules of a shock graph grammar. The grammar permits a reduction of a shock graph to a unique rooted shock tree. We introduce a novel tree matching algorithm which finds the best set of corresponding nodes between two shock trees in polynomial time. Using a diverse database of shapes, we demonstrate our systems performance under articulation, occlusion, and moderate changes in viewpoint.

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

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

6 Welche Ausschnitte gehören zu folgenden Titel ?

0 Seam Carving for Content-Aware Image Resizing

Ausschnitt(e): ....

Begründung(en): ....

1 Generic Model Abstraction from Examples

Ausschnitt(e): ....

Begründung(en): ....

2 Review of shape representation and description techniques

Ausschnitt(e): ....

Begründung(en): ....

3 Document image analysis: A primer

Ausschnitt(e): ....

Begründung(en): ....

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

Ausschnitt(e): ....

Begründung(en): ....

5 Curve Parameterization by Moments

Ausschnitt(e): ....

Begründung(en): ....

6 Measuring the Orientability of Shapes

Ausschnitt(e): ....

Begründung(en): ....

7 Increasing the discrimination power of the co-occurrence matrix-based features

Ausschnitt(e): ....

Begründung(en): ....

8 Shock Graphs and Shape Matching

Ausschnitt(e): ....

Begründung(en): ....

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

Ausschnitt(e): ....

Begründung(en): ....