

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 $e = (f \ g)$ $e=[f \ g]$

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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 = imclose(IM,SE)`

performs morphological closing on the grayscale or binary image IM, returning the closed 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.

`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.

`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. = imnoise(, 'salt & pepper', 0.1);

Begründung:

1. = medfilt2();

Begründung:

2. = conv2(, fspecial('gaussian', [5 5], 5));

Begründung:

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

Begründung:

4. = 1-im2bw(, 100/255);

Begründung:

5. = imhist(histeq(M));

Begründung:

6. = imclose(, strel('disk', 10));

Begründung:

7. = imopen(~ , strel('disk', 10));

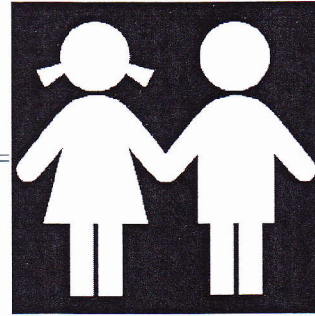
Begründung:

8. = bwdist();

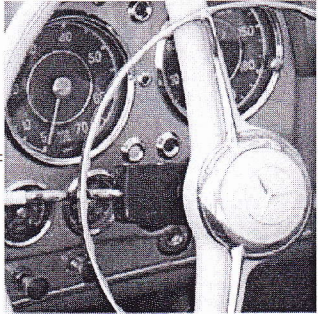
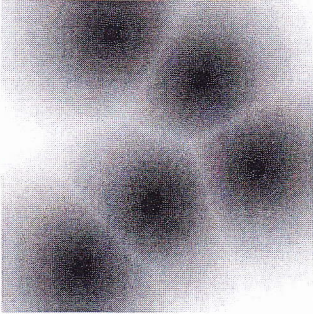


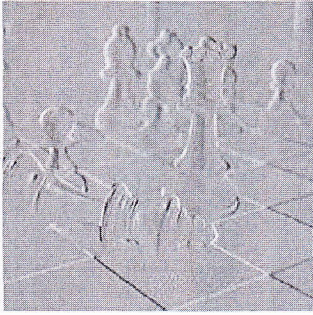
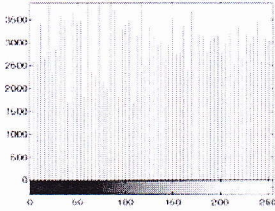
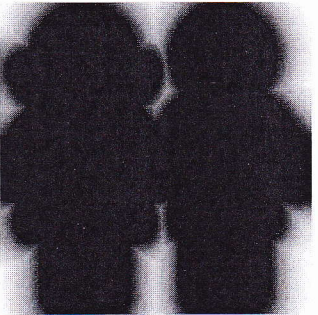
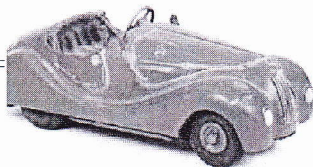
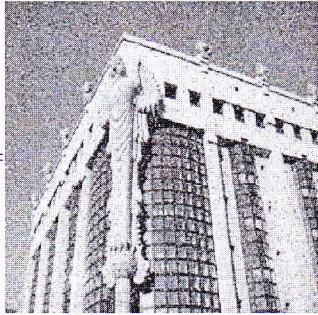
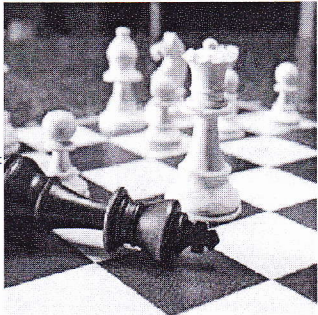
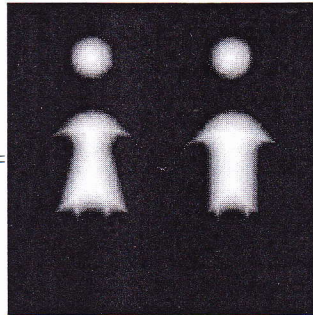
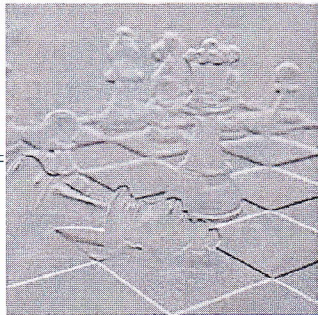
Begründung:

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

Begründung:

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

Grauwertbilder

<p>M=</p> 	<p>N=</p> 	<p>O=</p> 
<p>P=</p> 	<p>Q=</p> 	<p>R=</p> 
<p>S=</p> 	<p>T=</p> 	<p>U=</p> 
<p>V=</p> 	<p>W=</p> 	<p>X=</p> 

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2 Morphologische Transformation zu Gitter (5)

- 1. Sei $S = \text{mod}(M, 3) + 3 = \square$ der Abstand zwischen den Punkten eines Punktrasters.
- 2. Das Punktraster sei wie folgt definiert:

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

- 3. Zeichnen Sie alle 1-Punkte als \star im folgenden Bild B ein, das bereits einige Störpixel enthält:

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

Strukturelemente

							D						
							C						
							E						
											F		

- 4. Dieser Punktraster B soll in ein Liniengitter L umgewandelt werden, das die Rasterpunkte verbindet 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 \star definiert/ergänzt werden, wobei der Referenzpixel mit einem Buchstaben bezeichnet wird, der auch in den Operationen 1. bis 5. als Name des Strukturelements dient. Z.B. $Q = B \oplus C$. Alle zusätzlichen Pixel des Strukturelements werden durch \star eingetragen.
- 6. Welche Operationen sind notwendig, um aus dem gestörten Binärbild B das Liniengitter L zu produzieren (bis zu 4 Zwischenschritte können angegeben werden. Sollten nicht alle Störungen verschwinden, so kennzeichnen Sie alle verbleibenden!)?

- 1.
- 2.
- 3.
- 4.
- 5. $L =$

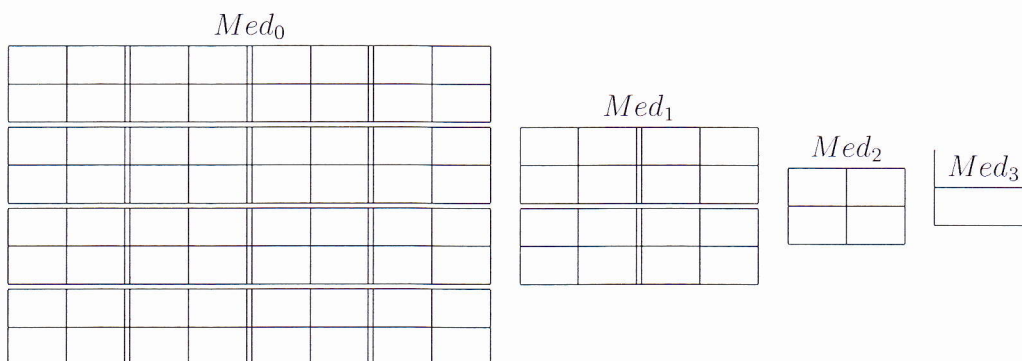
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3 Medianpyramide (5 P)

1. Die Häufigkeit der Grauwerte 1 bis 7 der Grundebene wird durch Ziffern Ihrer Matrikelnummer bestimmt: $H_0(g) = M_g, g = 1, 2, \dots, 7$. Der Rest der 8×8 -Grundebene wird mit 0 aufgefüllt.

$g =$	0	1	2	3	4	5	6	7
$H_0(g) =$								
$K_0(g) =$								
$H_1(g) =$								
$H_2(g) =$								

2. Zur Bestimmung des Median dient das kumulative Histogramm $K_0(g) = \sum_{i=0}^g H_0(i)$.
3. Die Histogramme der Ebenen 1 und 2 der $2 \times 2/4$ Medianpyramide werden durch $H_1(g) = [H_0(g)/4]$ und $H_2(g) = [H_0(g)/16]$ ermittelt. Beachte, dass 'ausgewogen' gerundet wird und die Gesamtpixelanzahl der jeweiligen Ebene genau 16 bzw. 4 sein muss!
4. An der Spitze der Pyramide steht der Median aller 64 Pixel der Grundebene.
5. Als Reduktionsfunktion soll der Median des 2×2 Reduktionsfensters dienen. Um ihn eindeutig zu machen, soll er mindestens zweimal im Reduktionsfenster auftreten.
6. Verteile die Grauwerte der Histogramme H_0, H_1, H_2 so auf die Ebenen der Medianpyramide, dass
- der Median jedes Reduktionsfensters genau dem Pixel darüber entspricht;
 - alle Ebenen mit beliebigem Schwellwert wohlgeformt sind.



7. (Optional für Zusatzpunkt) Welche Bedingungen muss der Median im kumulativen Histogramm $K_0(g)$ erfüllen?

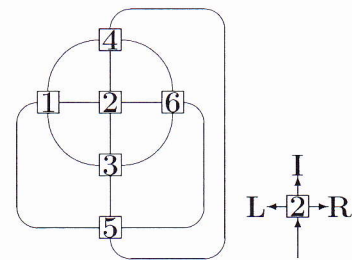
.....

.....

4 Pfade von Würfeln (5)

Ein Würfel wird auf einen Bildraster 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 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.



- Das folgende Bild ist durch den zuvor beschriebenen Prozess von mehreren verschiedenen Startpunkten aus erzeugt worden. Bestimmen Sie die maximal möglichen Würfelpfade von zwei Startpositionen aus in alle vier möglichen Richtungen. Die Pfade beschreiben Sie sowohl durch die Folge der Augenzahlen entlang des Pfades als auch durch die entsprechende RLI-Chain.

	0	1	2	3	4	5	6	7	8	9
1	1	6	2	1	1	3	6	4	1	3
2	2	2	1	4	5	5	5	4	2	5
3	6	4	4	4	6	4	6	3	1	4
4	5	5	6	2	2	2	6	5	2	3
5	1	3	3	3	1	3	1	3	1	1
6	2	2	1	5	1	5	5	5	5	4
7	6	4	3	2	4	4	6	4	6	6

Startpunkt $(1, M_1) = (1, \quad)$,

Richtung 0:

RLI-Chain:

Richtung 1:

RLI-Chain:

Richtung 2:

RLI-Chain:

Richtung 3:

RLI-Chain:

Startpunkt $(4, M_4) = (4, \quad)$,

Richtung 0:

RLI-Chain:

Richtung 1:

RLI-Chain:

Richtung 2:

RLI-Chain:

Richtung 3:

RLI-Chain:

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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 Many visual search and matching systems represent images using sparse sets of visual words: descriptors that have been quantized by assignment to the best-matching symbol in a discrete vocabulary. Errors in this quantization procedure propagate throughout the rest of the system, either harming performance or requiring correction using additional storage or processing. This paper aims to reduce these quantization errors at source, by learning a projection from descriptor space to a new Euclidean space in which standard clustering techniques are more likely to assign matching descriptors to the same cluster, and non-matching descriptors to different clusters.
- 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. Today's 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° (108.4°) 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 The ... operator-based edge detectors localize edges with the zero-crossings of the high-frequency components of image. One problem arising from this is that the noise contained in the high-frequency components will yield false zero-crossings. Noting that the amplitudes of high-frequency components of edges are relatively larger than that of noise, we may remove the low amplitudes of noise by thresholding the high-frequency components of an image.
- 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 Major differences exist between the moment approach to curve parameterization and the various Hough-transformtype methods. One important difference is that the moment approach uses no accumulator array and overall requires very little memory. Another is that the moment method does not depend on the sharpness or smoothness of edges and no edge-detection preprocessing step is necessary. (However, other types of preprocessing that reduce noise or otherwise simplify the image may be of use. Some examples are given in Section 5.) Still another point of distinction between our method and much previous work is that ours offers a unified treatment for all types of conics (circles, parabolas, etc.). However, perhaps a more fundamental difference is philosophical in nature, as the following example shows.

- 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 Characteristically, many attempts to implement Blum's original definition in the discrete world failed to preserve such fundamental properties as connectivity or Euclidean metrics. Basically, we can distinguish between four substantially different variants of skeletonization algorithms:
- (1) simulation of the 'grassfire';
 - (2) analytical computation of the medial axis;
 - (3) topological thinning; and
 - (4) medial axis extraction from a distance map.
- 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 Interest in computing parametric descriptions of lines and conics in images has been rekindled by new image coding schemes based on approximating images with geometrical elements such as wedgelets and curvelets [8], [31], [23] and by the opportunity to reduce ringing artifacts in compressed images [28]. For such applications, resistance to noise, computational speed, and memory requirements are major concerns. Moment-based techniques have long been recognized as well suited in this context, and an extensive body of theoretical and computational results has been developed.
- R This edge-matching filter should also make the value of the output noise variance σ_0^2 as small as possible. Similar to Canneys work [2], we define the criterion ρ as the improvement of signal-to-noise ratio from input to output at the location $n = 0$, where

$$\rho = \frac{h(0)}{\sum_{n=-N}^N h^2(N)} \quad (1)$$

- 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 Robust and time-efficient skeletonization of a (planar) shape, which is connectivity preserving and based on Euclidean metrics, can be achieved by first regularizing the Voronoi diagram (VD) of a shape's boundary points, i.e. by removal of noise-sensitive parts of the tessellation and then by establishing a hierarchic organization of skeleton constituents. Each component of the VD is attributed with a measure of prominence which exhibits the expected invariance under geometric transformations and noise. The second processing step, a hierarchic clustering of skeleton branches, leads to a multiresolution representation of the skeleton, termed skeleton pyramid.

6 Welche Ausschnitte gehören zu folgenden Titel ?

0 A Syntactic Approach to Scale-Space-Based Corner Description

Ausschnitt(e):

Begründung(en):

1 Robust distributed multi-view video compression for wireless camera networks

Ausschnitt(e):

Begründung(en):

2 Hierarchic Voronoi skeletons

Ausschnitt(e):

Begründung(en):

3 The JPEG 2000 Still Image Compression Standard

Ausschnitt(e):

Begründung(en):

4 Laplacian Operator-Based Edge Detectors

Ausschnitt(e):

Begründung(en):

5 Descriptor Learning for Efficient Retrieval

Ausschnitt(e):

Begründung(en):

6 Review of shape representation and description techniques

Ausschnitt(e):

Begründung(en):

7 Dissimilarity between two skeletal trees in a context

Ausschnitt(e):

Begründung(en):

8 Curve Parameterization by Moments

Ausschnitt(e):

Begründung(en):

9 Watershed segmentation using prior shape and appearance knowledge

Ausschnitt(e):

Begründung(en):