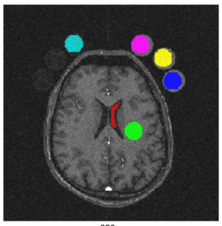
Results of measurements - SNR

Arvid Lundervold, University of Bergen, Norway

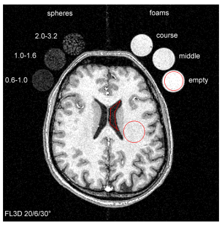
COST B11 - WG 3, Heidelberg 19-21 October, 2000

256



256

←



513

513

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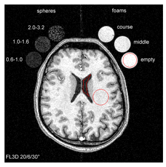
Data



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MAGNETOM VISION 1.5 T

```
12-JUL-2000   M 45Y
sequence = fl3d_6b195.wkc   TR/TE/FA = 20/6/30deg
Slice thickness: 1 mm ;     FoV 256*256 ; 32 slices  uses slice 4-29
                                                     SP -34 : slice 11

                                                     SNR
Series 2 (336-2-4,...,336-2-35)   : TA  10:57  AC 4  2.00  256 *256o
Series 3 (336-3-36,...,336-3-67)  : TA  05:30  AC 2  1.41  256 *256o
Series 4 (336-4-68,...,336-4-99)  : TA  02:46  AC 1  1.00  256 *256o

Series 6 (336-6-132,...,336-6-163) : TA  02:46  AC 2  128 *256o
Series 7 (336-7-164,...,336-7-195) : TA  06:11  AC 3  192 *256o
```

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Making the ROI mask in MaZda

from Tex05003.bmp (SP -34.0)

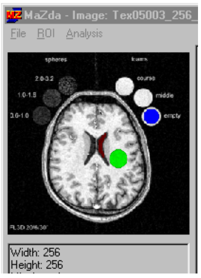
Make a 256x256 uint16 .raw out of Tex05003.bmp :

```
M = imread('../Tex05/Tex05003.bmp');
imshow(M)

M        513x513x3     789507  uint8 array

R = imresize(M,[256 256], 'bilinear');
imwrite(R,'../Tex05/Tex05003_256_roi.bmp','bmp');
S = rgb2gray(R);
S_us = uint16(fliplr(S'));
fid = fopen('../Tex05/Tex05003_256_roi.raw','wb','n');
fwrite(fid, S_us,'uint16');
fclose(fid);
```

then use MaZda to draw the ROIs



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… or, making the ROI mask in PowerPoint

from Tex05003.bmp

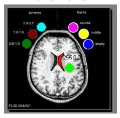
Insert Tex05003_256_roi.bmp (generated in Matlab)

or any other MR image file which PowerPoint can read

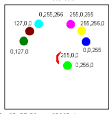
as a picture into PowerPoint with Page Setup:

Width: 2.68 inches
Hight: 2.68 inches
for a 256 x 256 image

PowerPoint



Matlab



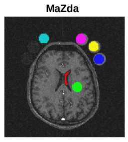
Tex05_3ROI_on_05003_ima_png.png

Then, (i) draw the masks (with specific RGB values),
(ii) delete the background .BMP image
(iii) save result as Portable Network Graphics (.PNG)

Finally, convert the .PNG file to .BMP (e.g. using Matlab)

The resulting .BMP file can then be loaded into MaZda ⟶

MaZda



Tex05_3ROI_on_05003_ima_png.bmp & 336-4-78.ima

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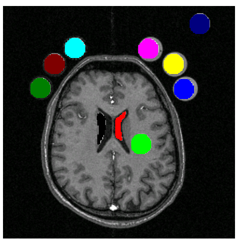
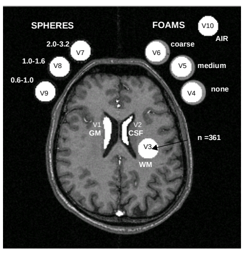
Matlab SNR analysis 10 ROIs



MASK: ../Tex05/Tex05_10ROI_png.png
IMAGE: ../Lodz_ftp/12_jul_00/336-4-078.raw
PPT: ../Tex05/Tex05_10ROI_on_annot_05003_ima.ppt



>> mshow(3* SNR_2_00 ./ max(max(SNR_2_00)) + ROI')

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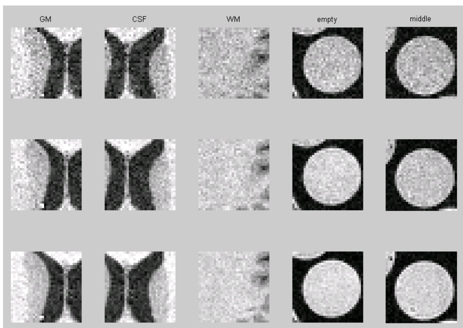
32 x 32 ROIs from 3D FLASH acquisitions with AC=1,2,4

SNR

1.00
(AC = 1)

1.41
(AC = 2)

2.00
(AC = 4)



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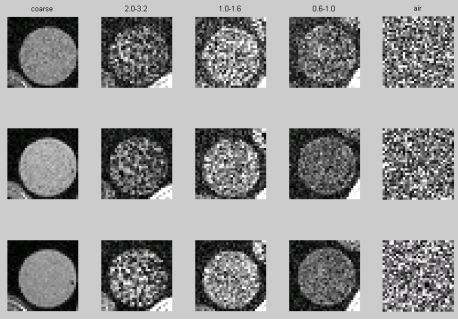
32 x 32 ROIs from 3D FLASH acquisitions with AC=1,2,4 cont.

SNR

1.00 (AC = 1)

1.41 (AC = 2)

2.00 (AC = 4)



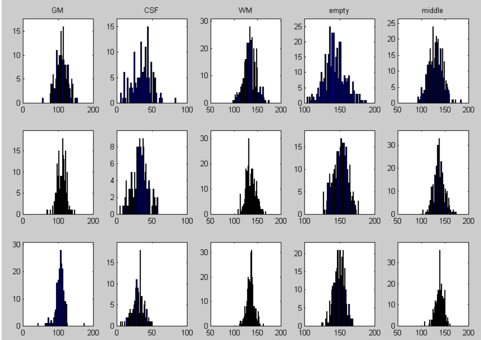
ROI-specific 3D FLASH signal intensity distributions vs. SNR

SNR

1.00

1.41

2.00



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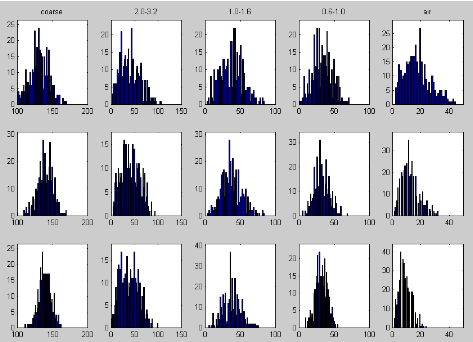
ROI-specific 3D FLASH signal intensity distributions vs. SNR cont.

SNR

1.00

1.41

2.00



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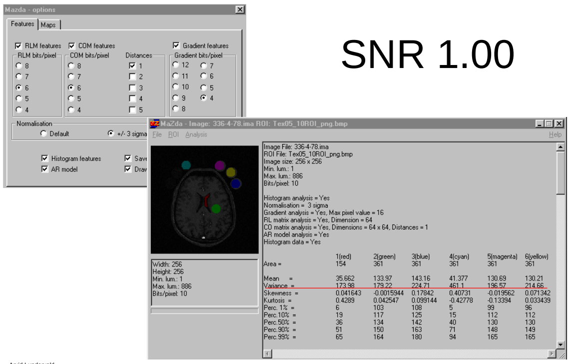

SNR 1.00

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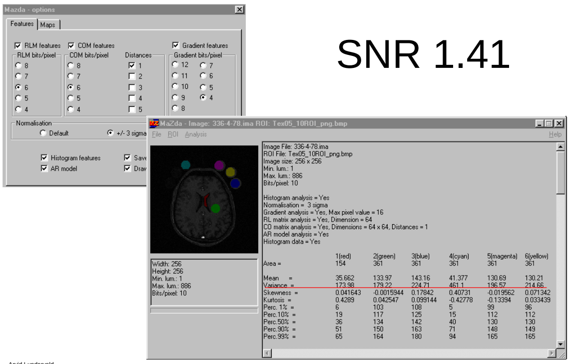

SNR 1.41

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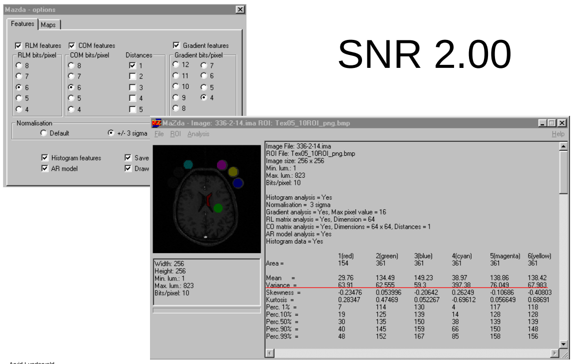

SNR 2.00

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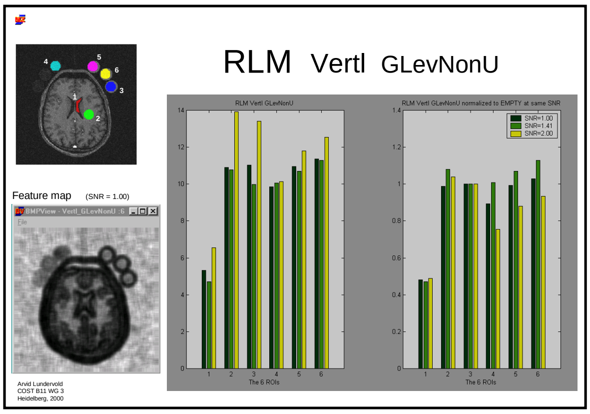
Heidelberg, 2000


RLM Vertl GLevNonU
Feature map (SNR = 1.00)
RLM Vertl GLevNonU
RLM Vertl GLevNonU normalized to EMPTY at same SNR
SNR=1.00
SNR=1.41
SNR=2.00
The 6 ROIs
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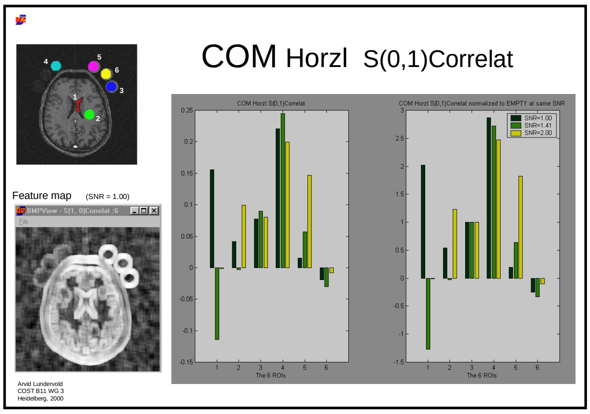
COM Horzl S(0,1)Correlat
Feature map (SNR = 1.00)
SNR=1.00
SNR=1.41
SNR=2.00
The 6 ROIs
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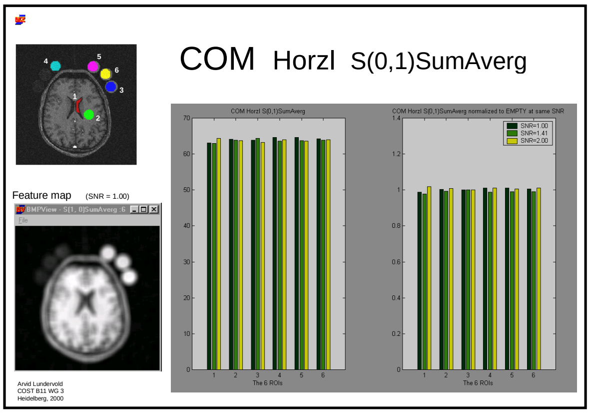
COM Horzl S(0,1)SumAverg
Feature map (SNR = 1.00)
SNR=1.00
SNR=1.41
SNR=2.00
The 6 ROIs
Arvid Lundervold
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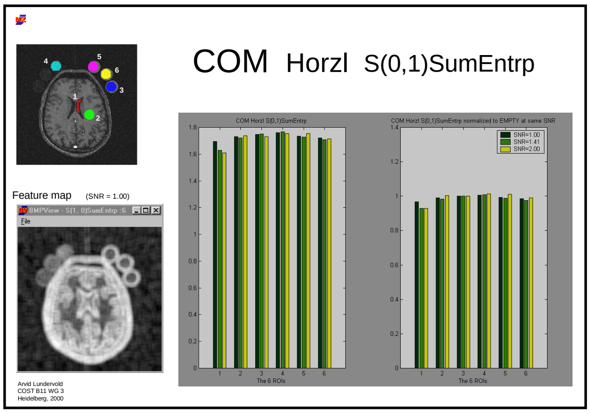
COM Horzl S(0,1)SumEntrp
Feature map (SNR = 1.00)
SNR=1.00
SNR=1.41
SNR=2.00
The 6 ROIs
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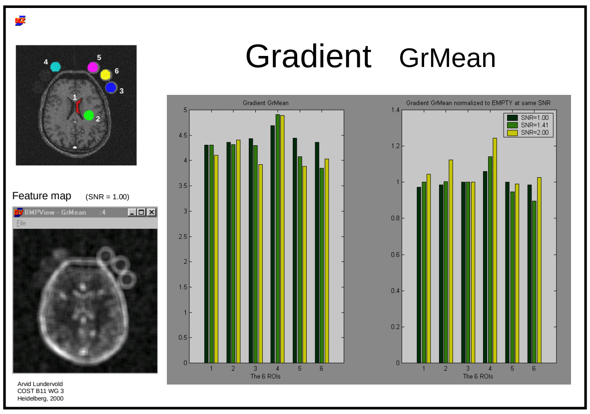
Gradient GrMean
Feature map (SNR = 1.00)
Gradient GrMean
Gradient GrMean normalized to EMPTY at same SNR
SNR=1.00
SNR=1.41
SNR=2.00
The 6 ROIs
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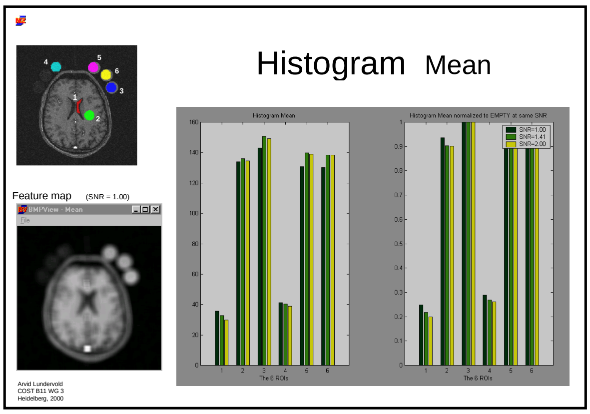
Histogram Mean
Feature map (SNR = 1.00)
Histogram Mean
Histogram Mean normalized to EMPTY at same SNR
SNR=1.00
SNR=1.41
SNR=2.00
The 6 ROIs
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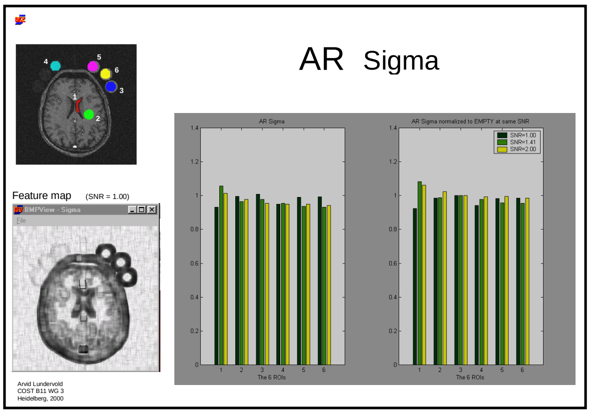
AR Sigma
Feature map (SNR = 1.00)
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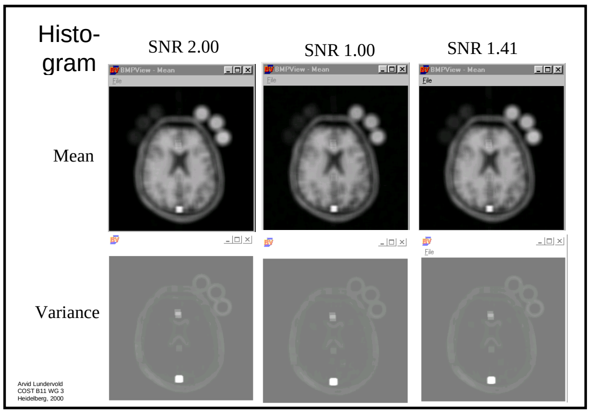
Histo-
gram
SNR 2.00
SNR 1.00
SNR 1.41
Mean
Variance
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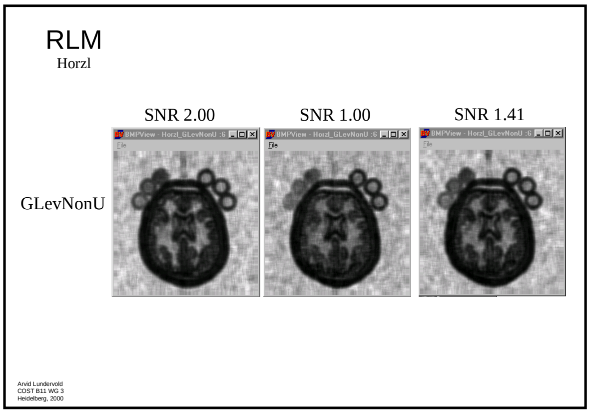
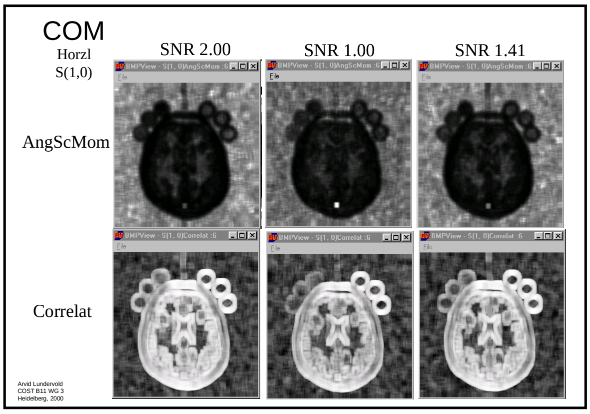
COST B11 WG 3
Heidelberg, 2000


RLM
Horzl
SNR 2.00
SNR 1.00
SNR 1.41
GLevNonU
Arvid Lundervold
COST B11 WG 3
Heidelberg, 2000


COM
Horzl
S(1,0)
SNR 2.00
SNR 1.00
SNR 1.41
AngScMom
Correlat
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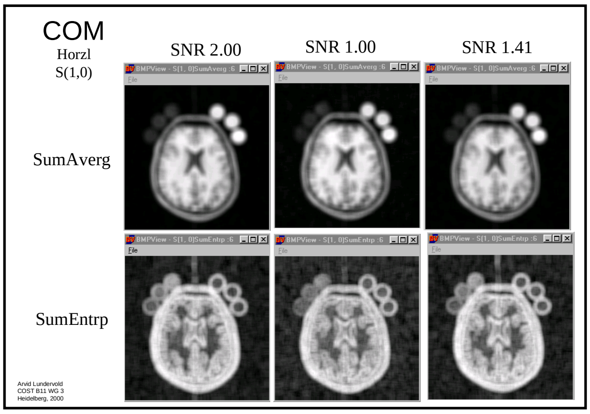
COM
Horzl
S(1,0)
SNR 2.00
SNR 1.00
SNR 1.41
SumAverg
SumEntrp
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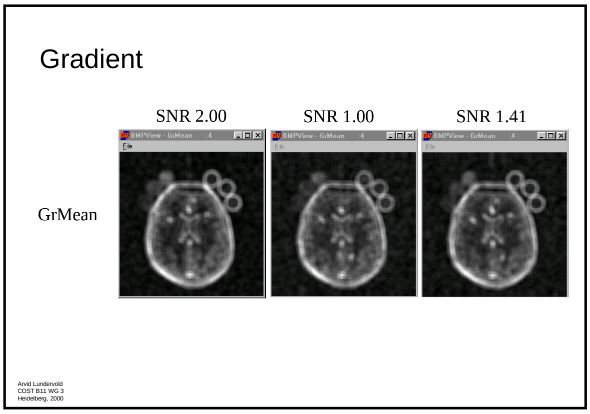
Gradient
SNR 2.00
SNR 1.00
SNR 1.41
GrMean
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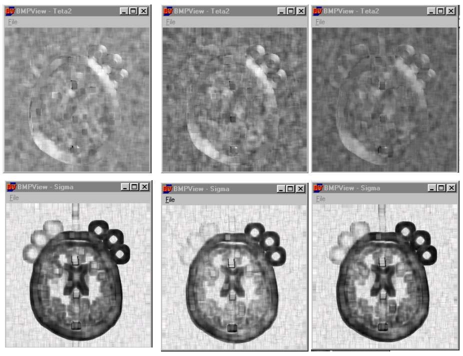
COST B11 WG 3
Heidelberg, 2000

AR

SNR 2.00 SNR 1.00 SNR 1.41

Teta2

Sigma



Conclusions

- Generally, texture is sensitive to SNR
- Some texture features are more robust to noise, than others (ROI dependence)
  - "Robust" Ex. COM Horzl S(0,1)SumEntrp
    AR Sigma
  - "Sensitive" Ex. COM Horzl S(0,1)Correlat
    RLM Vertl GLevNonU

Other experiments and observations will be reported in WG 1 ("Feature maps")

Definitions of texture parameters computed by MaZda :

Histogram

Histogram-based features

Note

To keep consistency with the formulas used in the standard references [1], [2] on texture analysis, it is assumed in MaZda that the intensity of image under analysis changes from 1 to Ng, where $Ng = 2^k$, and k is the number of bits per pixel. Thus if originally the image intensity changes from 0 to Ng-1, MaZda converts this image internally, such that its intensity changes from 1 to Ng. Consequently, the summation indices in the formulas listed below span the range from 1 to Ng.

In the formulas that follow, $p(i)$ is a normalized histogram vector (i.e. histogram whose entries are divided by the total number of pixels in ROI), i=1,2,..., N_g, and N_g denotes the number of intensity levels.

Mean: $\mu = \sum_{i=1}^{N_g} ip(i)$

Variance: $\sigma^2 = \sum_{i=1}^{N_g} (i-\mu)^2 p(i)$

Skewness: $\mu_3 = \sigma^{-3} \sum_{i=1}^{N_g} (i-\mu)^3 p(i)$

Kurtosis: $\mu_4 = \sigma^{-4} \sum_{i=1}^{N_g} (i-\mu)^4 p(i) - 3$

References

[1] R. Haralick, K. Shanmugam and I. Dinstein, Textural Features for Image Classification, *IEEE Transactions on Systems, Man and Cybernetics*, **3**, 6, 1973, 610-621.

[2] R. Haralick, Statistical and Structural Approaches to Texture, *Proceedings IEEE*, **67**, 5, 1979, 786-804.

[3] R. Lerski, K. Straughan, L. Shad, D. Boyce, S. Bluml and I. Zuna, MR Image Texture Analysis – An Approach to Tissue Characterization, *Magnetic Resonance Imaging*, **11**, 1993, 873-887.

[4] A. Materka and M. Strzelecki, *Texture Analysis Methods – A Review*, COST B11 report (presented and distributed at MC meeting and workshop in Brussels, June 1998), Technical University of Lodz, Poland, 1998.

[5] Y. Hu and T. Dennis, Textured Image Segmentation by Context Enhanced Clustering, *IEE Proc.-Visual Image and Signal Processing*, **141**, 6, 1994, 413-421.

Gradient

Gradient-based parameters

For the gradient feature calculation the following neighborhood for image pixel $x(i,j)$ is defined:

A	B	C	D	E
F	G	H	I	J
K	L	$x(i,j)$	N	O
P	Q	R	S	T
U	V	W	Y	Z

Based on this neighborhood, the absolute gradient value (*ABSV(i,j)*) is calculated for each pixel:

a) for 5x5 pixel neighborhood: $ABSV5(i,j) = \sqrt{(W-C)^2 + (O-K)^2}$

b) for 3x3 pixel neighborhood: $ABSV3(i,j) = \sqrt{(R-H)^2 + (N-L)^2}$

The *ABSV3* definition is used in MaZda version 2.13. For the *ABSV*=*ABSV3* matrix of *M* elements (which contains absolute gradient values for ROI pixels), the gradient features are defined as follows:

Mean absolute gradient: $\text{GrMean} = \frac{1}{M} \sum_{i,j \in ROI} ABSV(i,j)$

Variance of absolute gradient: $\text{GrVariance} = \frac{1}{M} \sum_{i,j \in ROI} (ABSV(i,j) - \text{GrMean})^2$

Skewness of absolute gradient:
$\text{GrSkewness} = \frac{1}{(\sqrt{\text{GrVariance}})^3} \frac{1}{M} \sum_{i,j \in ROI} (ABSV(i,j) - \text{GrMean})^3$

Kurtosis of absolute gradient:
$\text{GrKurtosis} = \frac{1}{(\sqrt{\text{GrVariance}})^4} \frac{1}{M} \sum_{i,j \in ROI} (ABSV(i,j) - \text{GrMean})^4 - 3$

where *ROI* is a region of interest.

Percentage of non-zero *ABSV* matrix elements (**Grads>0**)

RLM

Run length matrix-based parameters

Let $p(i,j)$ be the number of times there is a run of length j having grey level i. Let N_g be the number of grey levels and N_r be the number of runs. Definitions of the parameters of the run-length matrix $p(i,j)$, as adopted in MaZda, are given below.

Short run emphasis inverse moments: $\text{ShrtREmph} = (\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \frac{p(i,j)}{j^2}) / C$

Long run emphasis moments: $\text{LngREmph} = (\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} j^2 p(i,j)) / C$

Grey level nonuniformity: $\text{GLevNonUni} = (\sum_{i=1}^{N_g} (\sum_{j=1}^{N_r} p(i,j))^2) / C$

Run length nonuniformity: $\text{RLNonUni} = (\sum_{j=1}^{N_r} (\sum_{i=1}^{N_g} p(i,j))^2) / C$

Fraction of image in runs: $\text{Fraction} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j) / \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} jp(i,j)$

The coefficient C is defined as $C = \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)$

The above five features are calculated for four directions: horizontal (Horzl_), vertical (Vertl_), slanted at 45 degrees (45dgr_) and slanted at 135 degrees (135dgr_). The RL feature name in MaZda software contains a prefix that defines direction and feature type, for example 45dgr_RLNonUni means the run length nonuniformity calculated for 45-degree direction.

The second-order histogram is defined as the co-occurrence matrix $h_{d\theta}(i,j)$ [1]. When divided by the total number of neighboring pixels $R(d, \theta)$ in ROI, this matrix becomes the estimate of the joint probability, $p_{d\theta}(i,j)$, of two pixels, a distance d apart along a given direction θ having particular (co-occurring) values i and j. Formally, given the image $f(x,y)$ with a set of N_g discrete intensity levels, the matrix $h_{d\theta}(i,j)$ is defined such that its (i,j)th entry is equal to the number of times that

$f(x_1, y_1) = i$ and $f(x_2, y_2) = j$,

where $(x_2, y_2) = (x_1, y_1) + (d \cos\theta, d \sin\theta)$.

This yields a square matrix of dimension equal to the number of intensity levels in the image, for each distance d and orientation θ. In MaZda, the distances d = 1, 2, 3, 4 and 5 pixels with angles θ = 0°, 45°, 90° and 135° are considered. Reduction of the number of intensity levels (by quantization to fewer levels of intensity) helps increase the speed of computation, with some loss of textural information.

The co-occurrence matrix-derived parameters computed by MaZda are defined by the equations that follow, where μ_x, μ_y and σ_x, σ_y denote the mean and standard deviations of the row and column sums of the co-occurrence matrix, respectively [related to the marginal distributions $p_x(i)$ and $p_y(j)$]. R is the total number of neighboring pixel pairs, which normalizes the co-occurrence matrix to the probability distribution.

COM

Entropy: $\text{Entropy} = -\frac{1}{R} \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \log(\frac{1}{R} p(i,j))$

Difference variance: $\text{DifVarnc} = \sum_{i=0}^{N_g-1} (i - \mu_{x-y})^2 p_{x-y}(i)$

where μ_{x-y} is a mean value of difference distribution p_{x-y}:

$p_{x-y}(k) = \frac{1}{R} \sum_{\substack{i=1 \\ |i-j|=k}}^{N_g} \sum_{j=1}^{N_g} p(i,j) \qquad k = 0,1,\ldots,N_g - 1$

Co-occurrence matrix-derived parameters

Angular second moment: $\text{AngScMom} = \frac{1}{R^2} \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j)^2$

Contrast: $\text{Contrast} = \frac{1}{R} \sum_{n=0}^{N_g-1} n^2 \sum_{\substack{i=1 \\ |i-j|=n}}^{N_g} \sum_{j=1}^{N_g} p(i,j)$

Correlation: $\text{Correlat} = \frac{\frac{1}{R} \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} ijp(i,j) - \mu_x \mu_y}{\rho_x \rho_y}$

Sum of squares: $\text{SumOfSqs} = \frac{1}{R} \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i - \mu_x)^2 p(i,j)$

Inverse difference moment: $\text{InvDfMom} = \frac{1}{R} \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{1}{1+(i-j)^2} p(i,j)$

Sum average: $\text{SumAverg} = \sum_{i=1}^{2N_g} ip_{x+y}(i)$,

where $p_{x+y}(k) = \frac{1}{A} \sum_{\substack{i=1 \\ i+j=k}}^{N_g} \sum_{j=1}^{N_g} p(i,j) \qquad k = 2,3\ldots,2N_g$

Sum variance: $\text{SumVarnc} = \sum_{i=1}^{2N_g} (i - x_6)^2 p_{x+y}(i)$

Sum entropy: $\text{SumEntrp} = -\sum_{i=1}^{2N_g} p_{x+y}(i) \log(p_{x+y}(i))$

Difference entropy: $\text{DifEntrp} = -\sum_{i=1}^{N_g} p_{x-y}(i) \log(p_{x-y}(i))$

AR

Autoregressive model parameters

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The autoregressive (AR) model assumes a local interaction between image pixels in that pixel intensity is a weighted sum of neighbouring pixel intensities. Assuming image f is a zero-mean random field, an AR causal model can be defined as

$$f_s = \sum_{r \in N_s} \theta_r f_r + e_s$$

where f_s is image intensity at site s, e_s denotes an independent and identically distributed (i.i.d.) noise, N_s is a neighbourhood of s, and $\boldsymbol{\theta}$ is a vector of model parameters. The local neighbourhood for AR model implemented in MaZda, represented by 4 parameters, is shown in Fig. 7.1. Shaded area in Fig. 7.1 indicates region where valid causal half-plane AR model neighbourhood may be located, in general.

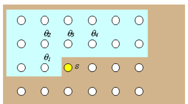

Fig. 7.1. Local neighbourhood of image element f_s

Using the AR model for image segmentation consists in identifying the model parameters for a given image region and then using the obtained parameter values for texture discrimination. In the case of simple pixel neighbourhood shown in Fig. 7.1, that comprises 4 immediate pixel neighbours, there are 5 unknown model parameters – the standard deviation σ of the driving noise e_s and the model parameter vector $\boldsymbol{\theta}=[\theta_1,\theta_2,\theta_3,\theta_4]$. The parameters can be estimated by minimizing the sum of squared error

$$\sum_s e_s^2 = \sum_s \left(f_s - \hat{\boldsymbol{\theta}} \boldsymbol{w}_s\right)^2$$

which leads to the following linear equations:

$$\hat{\boldsymbol{\theta}} = \left(\sum_s \boldsymbol{w}_s \boldsymbol{w}_s^T\right)^{-1} \left(\sum_s \boldsymbol{w}_s f_s\right)$$

$$\hat{\sigma}^2 = N^{-2} \sum_s \left(f_s - \hat{\boldsymbol{\theta}} \boldsymbol{w}_s\right)^2$$

where $\boldsymbol{w}_s = \mathrm{col}[f_i, i \in N_s]$, and the square $N \times N$ image is assumed. The above set of equations is numerically solved in MaZda for each ROI of interest.

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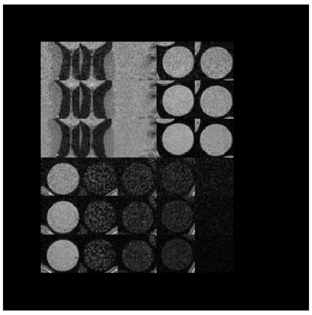
Mosaic (10 ROIs x 3 SNR)



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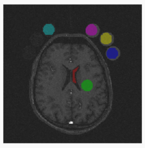
Series 4 (336-4-78) TA 02:46 AC 1 SNR: 1.00

MaZda - Image: 336-4-78.ima ROI: Tex05_3ROI_on_05003_ima_png.bmp

File ROI Analysis Help



Width: 256
Height: 256
Min. lum.: 1
Max. lum.: 886
Bits/pixel: 10

Image File: 336-4-78.ima
ROI File: Tex05_3ROI_on_05003_ima_png.bmp
Image size: 256 x 256
Min. lum.: 1
Max. lum.: 886
Bits/pixel: 10

Histogram analysis = Yes
Normalisation = 3 sigma
Gradient analysis = Yes, Max pixel value = 16
RL matrix analysis = Yes, Dimension = 64
CO matrix analysis = Yes, Dimensions = 64 x 64, Distances = 1 2 3 4 5
AR model analysis = Yes
Histogram data = Yes

	1(red)	2(green)	3(blue)	4(cyan)	5(magenta)	6(yellow)
Area =	154	361	361	361	361	361
Mean =	35.662	133.97	143.16	41.377	130.69	130.21
Variance =	173.98	179.22	224.71	461.1	196.57	214.66
Skewness =	0.041643	-0.0015944	0.17842	0.40731	-0.019562	0.071342
Kurtosis =	0.4289	0.042547	0.099144	-0.42778	-0.13394	0.033439
Perc. 1% =	6	103	108	5	99	96
Perc.10% =	19	117	125	15	112	112
Perc.50% =	36	134	142	40	130	130
Perc.90% =	51	150	163	71	148	149
Perc.99% =	65	164	180	94	165	165

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BMPView - Histogram drawing

SNR: 1.00

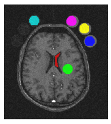
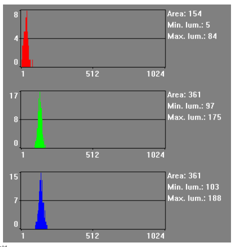
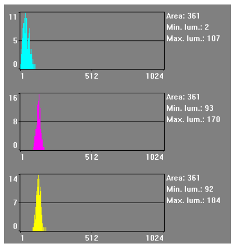


Image: 336-4-78.ima
ROI: Tex05_3ROI_on_05003_ima_png.bmp





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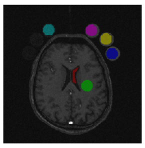
Series 3 (336-3-46) TA 05:30 AC 2 SNR: 1.41

MaZda - Image: 336-3-46.ima ROI: Tex05_3ROI_on_05003_ima_png.bmp

File ROI Analysis Help



Width: 256
Height: 256
Min. lum.: 1
Max. lum.: 863
Bits/pixel: 10

Image File: 336-3-46.ima
ROI File: Tex05_3ROI_on_05003_ima_png.bmp
Image size: 256 x 256
Min. lum.: 1
Max. lum.: 863
Bits/pixel: 10

Histogram analysis = Yes
Normalisation = 3 sigma
Gradient analysis = Yes, Max pixel value = 16
RL matrix analysis = Yes, Dimension = 64
CO matrix analysis = Yes, Dimensions = 64 x 64, Distances = 1 2 3 4 5
AR model analysis = Yes
Histogram data = Yes

	1(red)	2(green)	3(blue)	4(cyan)	5(magenta)	6(yellow)
Area =	154	361	361	361	361	361
Mean =	32.779	135.97	150.59	40.404	139.73	138.27
Variance =	110.02	111.91	105.64	389.04	123.14	127.61
Skewness =	-0.16089	0.16555	-0.032063	0.22594	-0.23144	0.017558
Kurtosis =	-0.050793	-0.16699	-0.40312	-0.76512	0.2829	0.44104
Perc. 1% =	9	113	127	6	111	111
Perc.10% =	19	124	136	14	126	124
Perc.50% =	34	136	151	38	140	138
Perc.90% =	46	151	164	69	153	153
Perc.99% =	57	161	173	85	166	168

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BMPView - Histogram drawing

SNR: 1.41

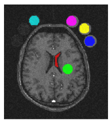
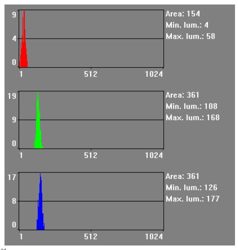
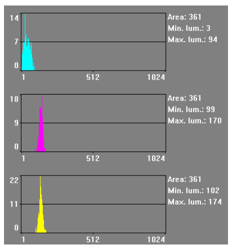


Image: 336-3-46.ima
ROI: Tex05_3ROI_on_05003_ima_png.bmp





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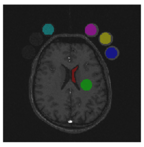
Series 2 (336-2-14) TA 10:57 AC 4 SNR: 2.00

MaZda - Image: 336-2-14.ima ROI: Tex05_3ROI_on_05003_ima_png.bmp

File ROI Analysis Help



Width: 256
Height: 256
Min. lum.: 1
Max. lum.: 823
Bits/pixel: 10

Image File: 336-2-14.ima
ROI File: Tex05_3ROI_on_05003_ima_png.bmp
Image size: 256 x 256
Min. lum.: 1
Max. lum.: 823
Bits/pixel: 10

Histogram analysis = Yes
Normalisation = 3 sigma
Gradient analysis = Yes, Max pixel value = 16
RL matrix analysis = Yes, Dimension = 64
CO matrix analysis = Yes, Dimensions = 64 x 64, Distances = 1 2 3 4 5
AR model analysis = Yes
Histogram data = Yes

	1(red)	2(green)	3(blue)	4(cyan)	5(magenta)	6(yellow)
Area =	154	361	361	361	361	361
Mean =	29.76	134.49	149.23	38.97	138.86	138.42
Variance =	63.91	62.555	59.3	397.38	76.049	67.983
Skewness =	-0.23476	0.053996	-0.20642	0.26249	-0.10686	-0.40803
Kurtosis =	0.28347	0.47469	0.052267	-0.69612	0.056649	0.68691
Perc. 1% =	7	114	130	4	117	118
Perc.10% =	19	125	139	14	128	128
Perc.50% =	30	135	150	38	139	139
Perc.90% =	40	145	159	66	150	148
Perc.99% =	48	152	167	85	158	156

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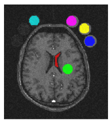
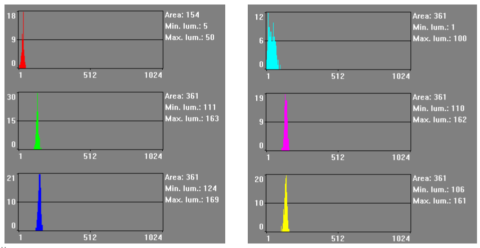
BMPView - Histogram drawing

SNR: 2.00

Image: 336-2-14.ima
ROI: Tex05_3ROI_on_05003_ima_png.bmp





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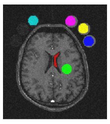
Mean

MaZda vs. Matlab



		1(red)	2(green)	3(blue)	4(cyan)	5(mag.)	6(yellow)
	Area =	154	361	361	361	361	361
SNR 1.00	Mean =	35.662	133.97	143.16	41.377	130.69	130.21
SNR 1.41	Mean =	32.779	135.97	150.59	40.404	139.73	138.27
SNR 2.00	Mean =	29.76	134.49	149.23	38.97	138.86	138.42

	red CSF	green WM	blue Empty	cyan Coarse	mag 2.0-3.2	yellow Middle
SNR 1.00 Mean =	35.662338	133.969529	143.163435	41.376731	130.686981	130.207756
SNR 1.41 Mean =	32.779221	135.972299	150.587258	40.404432	139.725762	138.274238
SNR 2.00 Mean =	29.759740	134.490305	149.227147	38.969529	138.858726	138.418283

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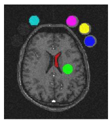
Variance

MaZda vs. Matlab



		1(red)	2(green)	3(blue)	4(cyan)	5(mag.)	6(yellow)
	Area =	154	361	361	361	361	361
SNR 1.00	Variance =	173.98	179.22	224.71	461.1	196.57	214.66
SNR 1.41	Variance =	110.02	111.91	105.64	389.04	123.14	127.61
SNR 2.00	Variance =	63.91	62.555	59.3	397.38	76.049	67.983

	red CSF	green WM	blue Empty	cyan Coarse	mag 2.0-3.2	yellow Middle
SNR 1.00 Var =	173.976893	179.215138	224.712901	461.104611	196.569609	214.663209
SNR 1.41 Var =	110.016192	111.910590	105.638508	389.038651	123.135320	127.606234
SNR 2.00 Var =	63.909808	62.554615	59.300205	397.381343	76.049294	67.982934

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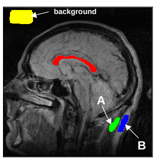
SNR and CNR



The **noise standard deviation** σ_0 of the signal in any voxel due to $N(0, \sigma_m^2)$ Gaussian noise added to the *k*-space data is independent of position in the image.

In a homogeneous region of a tissue of interest in the image, the average voxel signal over that region is a good estimate of the **tissue voxel signal** *S*.

Signal-to-noise ratio: $\mathrm{SNR} = S / \sigma_0$

A good way to measure σ_0 is to measure the mean value of a ROI outside the object where there is no signal. The voxel signal here is *Rayleigh* distributed in the magnitude image with mean $1.253\,\sigma_0$ and standard deviation $0.665\,\sigma_0$

Gudbjartsson & Patz (1995)
Haacke et al., (1999) p.340

Contrast between tissue **A** and tissue **B**: $C_{AB} = S_A - S_B$

Contrast-to-noise ratio: $\mathrm{CNR}_{AB} \equiv \frac{C_{AB}}{\sigma_0} = \frac{S_A - S_B}{\sigma_0} = \mathrm{SNR}_A - \mathrm{SNR}_B$

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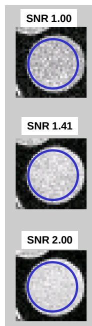
Normalization of the data

to the signal of the foam-empty tube



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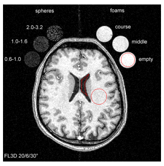
Experiment - II



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MAGNETOM VISION 1.5 T

20-SEP-2000 M 45Y
sequence = fl3d_6b195.wkc
Slice thickness: 1 mm ; FoV 256*256

SP: -54.0

```
TEX06001.ima : TA  08:14   AC  2  256 *256o  30/06/30deg
TEX06002.ima : TA  08:14   AC  2  256 *256o  30/16/30deg
TEX06003.ima : TA  08:14   AC  2  256 *256o  30/06/15deg
TEX06004.ima : TA  10:57   AC  2  256 *256o  40/06/30deg
```

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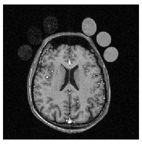
Experiment II cont.

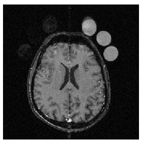
```
E2_1 = al_read_raw_img('../Tex06/TEX06001_us.raw',256,256,'uint16',1);
imagesc(E2_1, [0 300]), colormap(gray), axis image, axis off;
```

30/06/30º



TEX06001.ima

30/16/30º

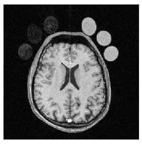


TEX06002.ima

30/06/15º

TEX06003.ima

40/06/30º



TEX06004.ima

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