Significance of Image Normalization in Texture Analysis

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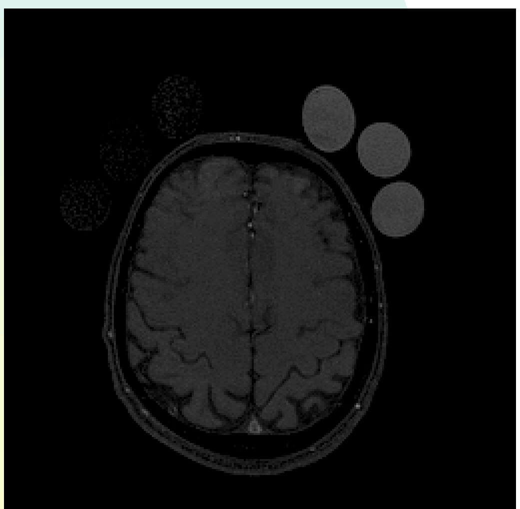
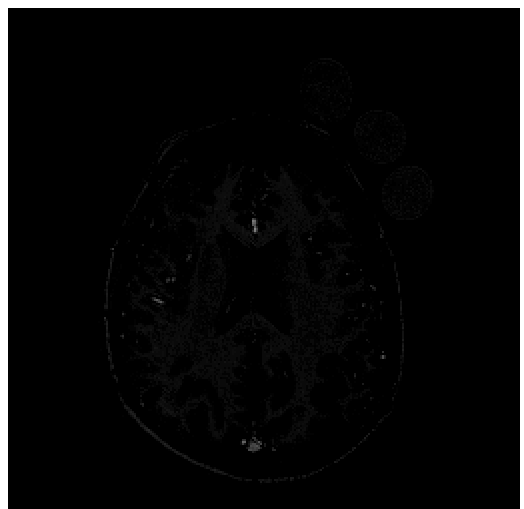
Aim of the study

- **to investigate the influence of image normalization on texture parameters**

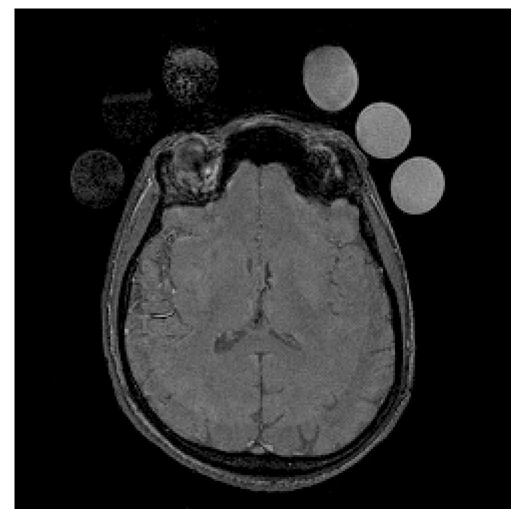
Motivation:
Large differences in image brightness (mean) and contrast (variance) in real-world images.



399-3-10.ima



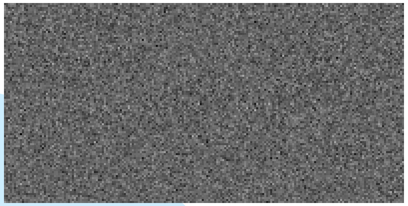
399-3-28.ima

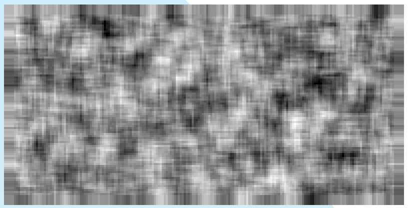


399-3-37.ima

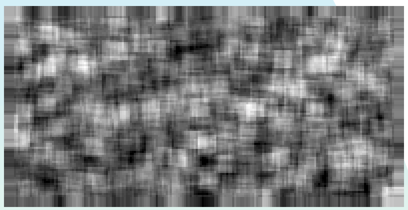
Gaussian noise image ***N1***

m=100, s=20

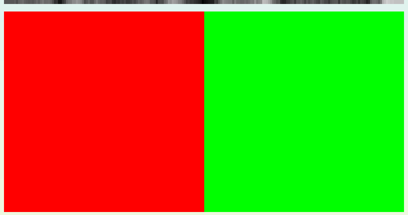




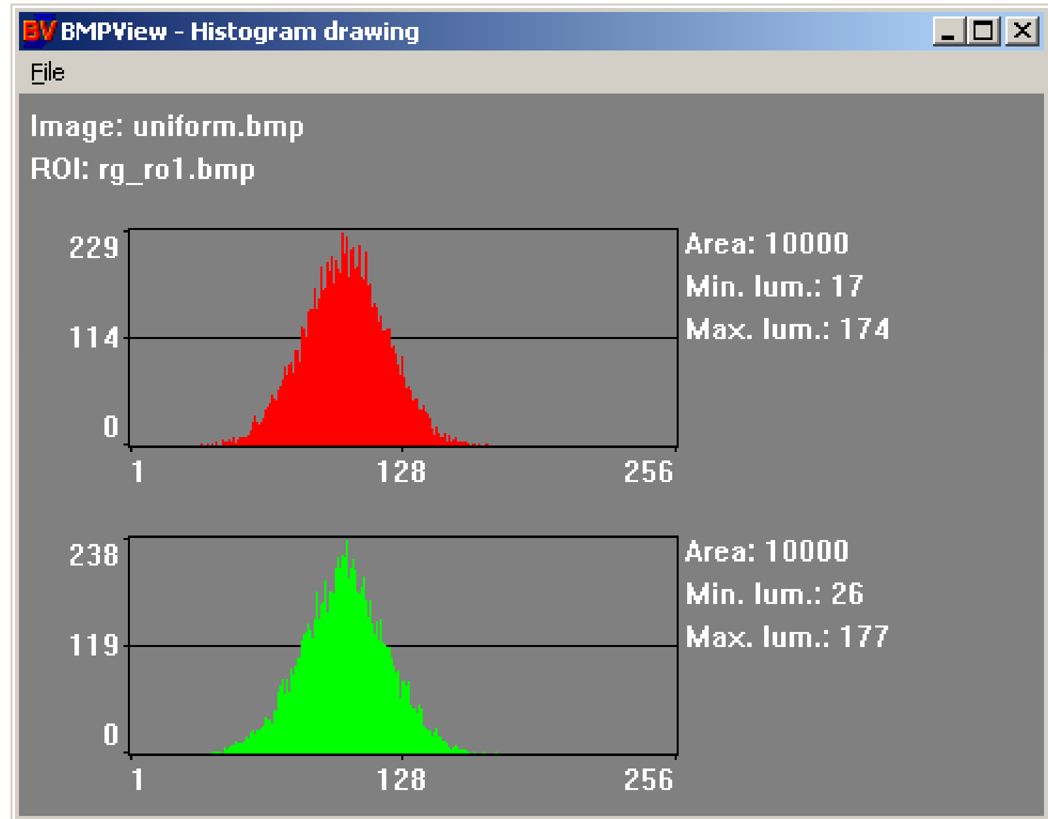
local mean

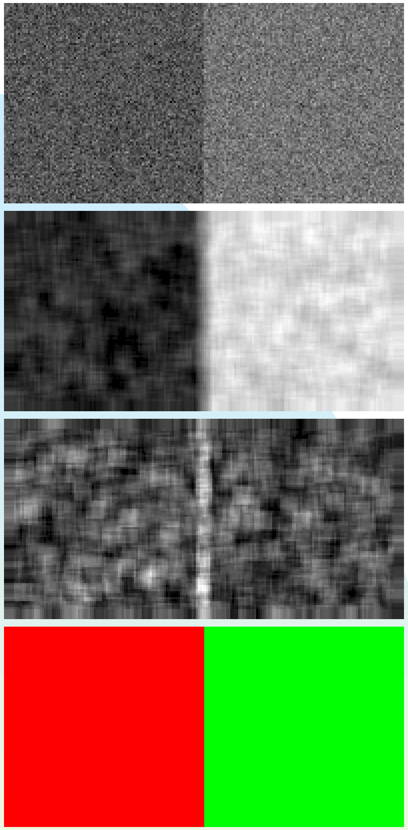


local variance



2 ROIs





noise image ***N2***

m1=85, m2=115

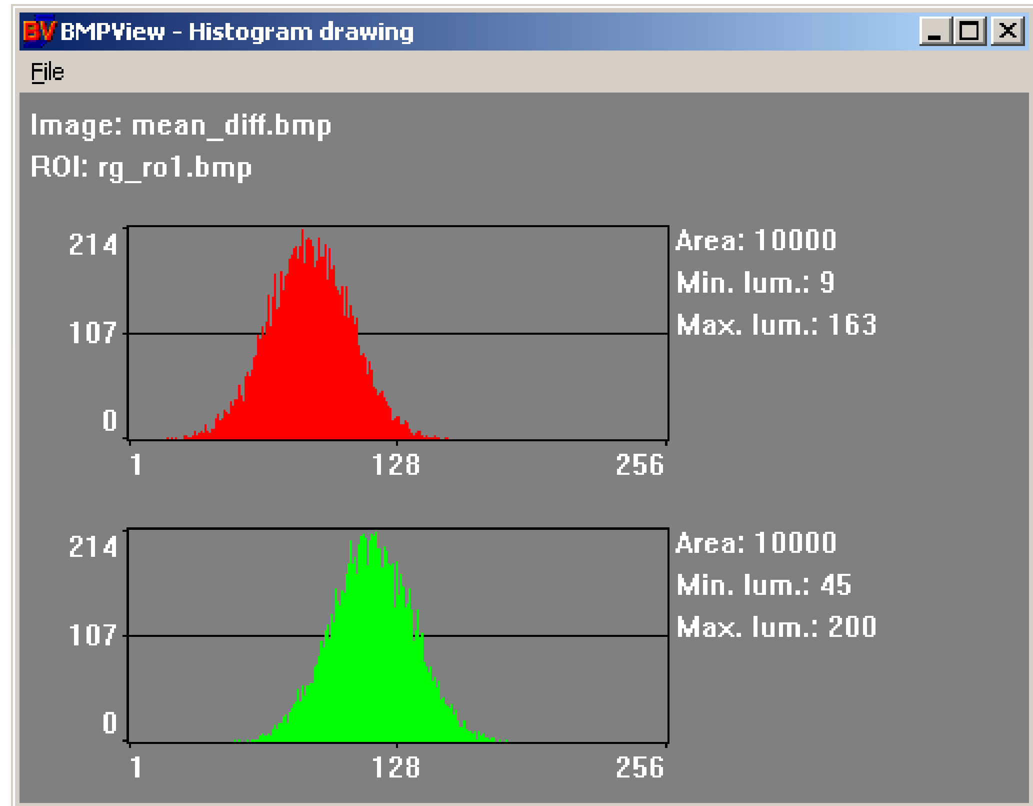
s1=s2=20

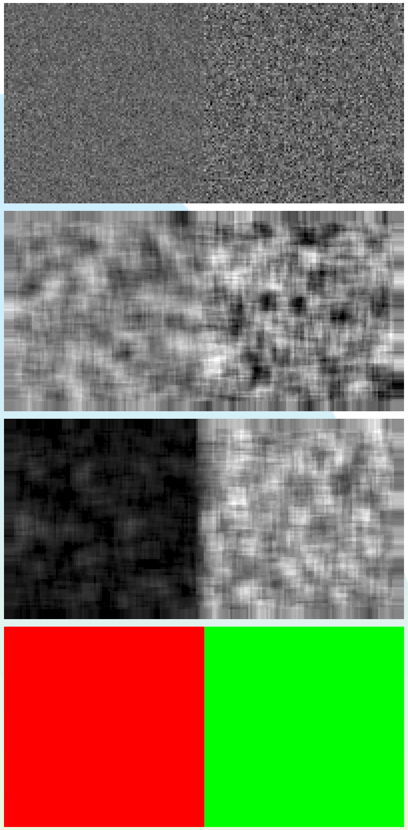
local mean

local variance

Difference in mean.

No actual difference in texture!





noise image ***N3***

m1=m2=100

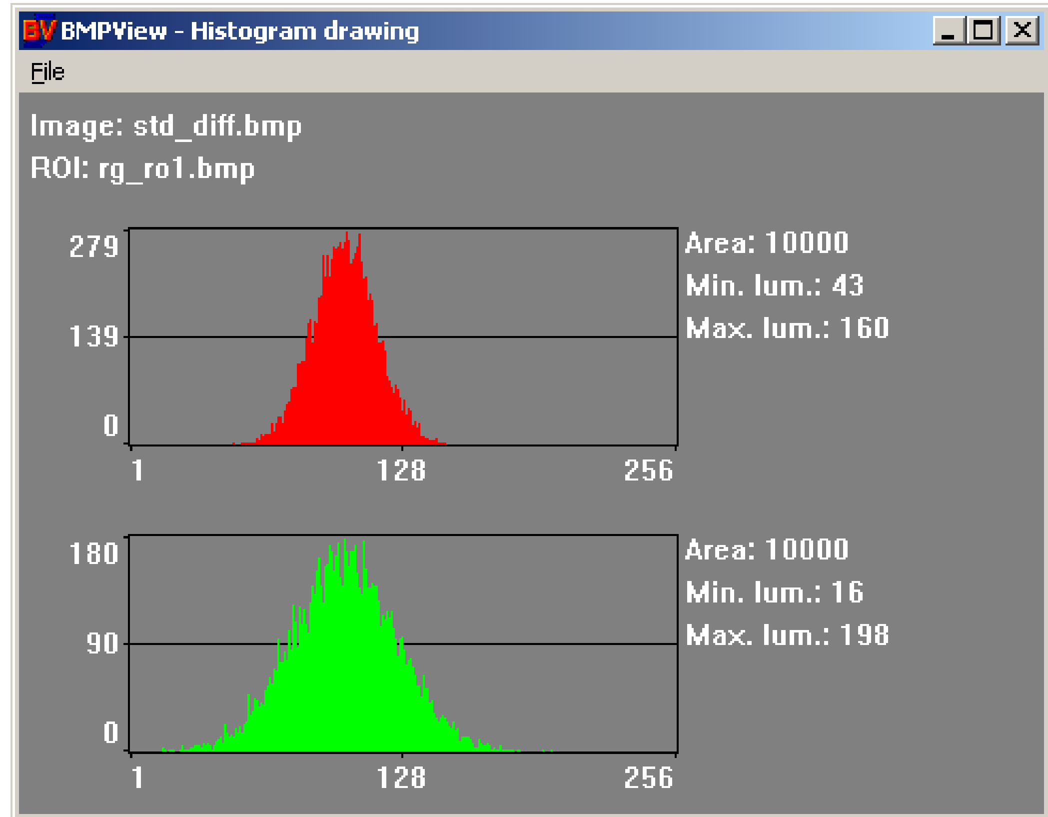
s1=15, s2=25

local mean

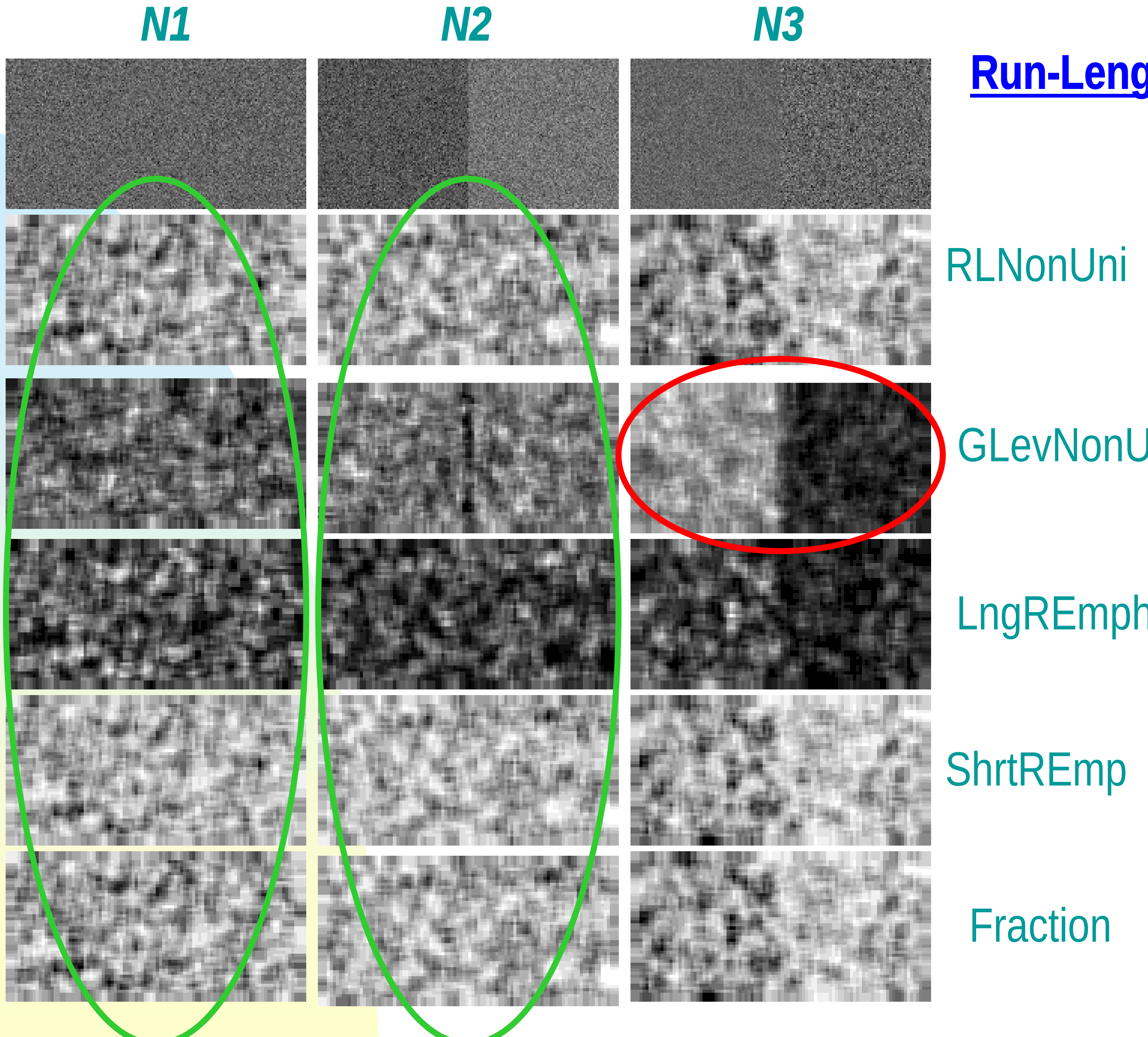
local variance

Difference in variance.

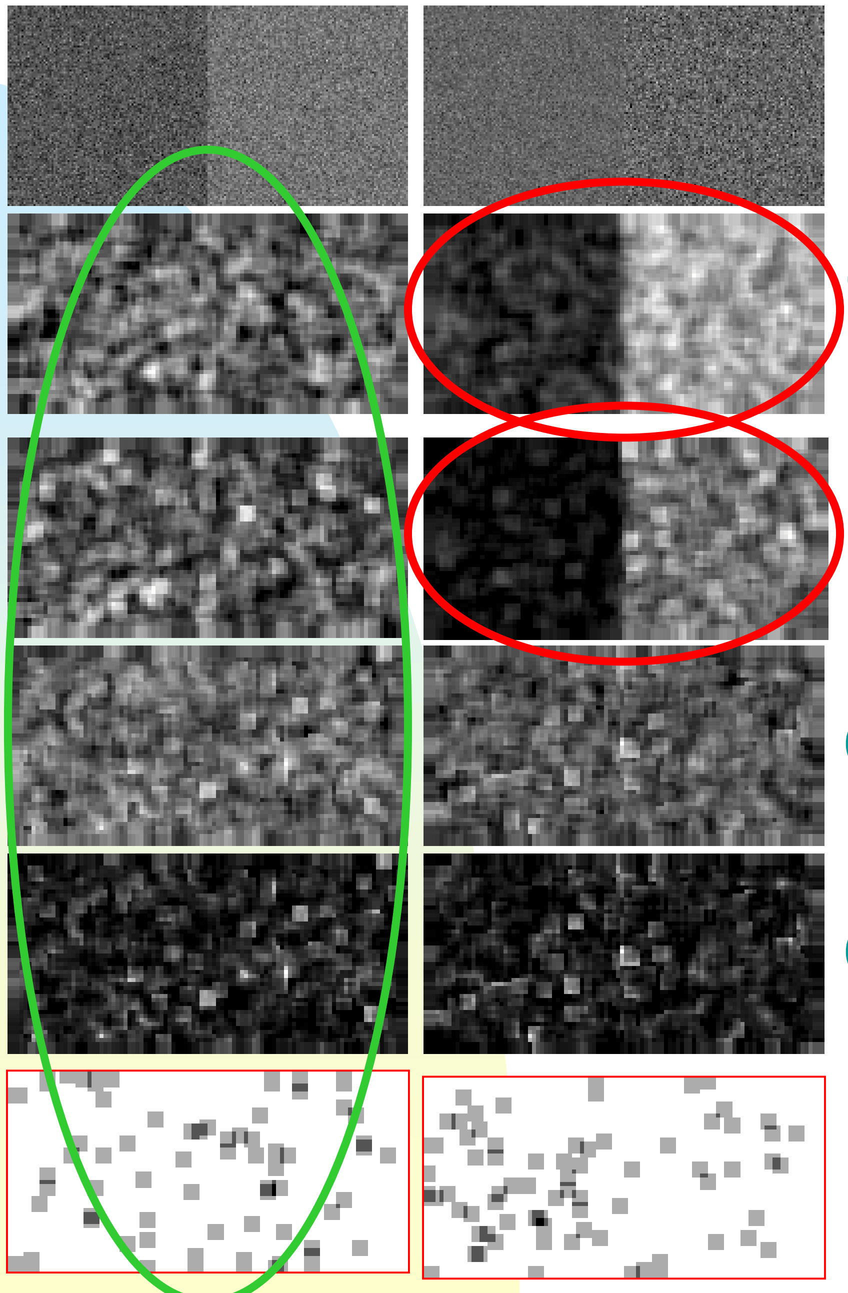
No actual difference in texture!

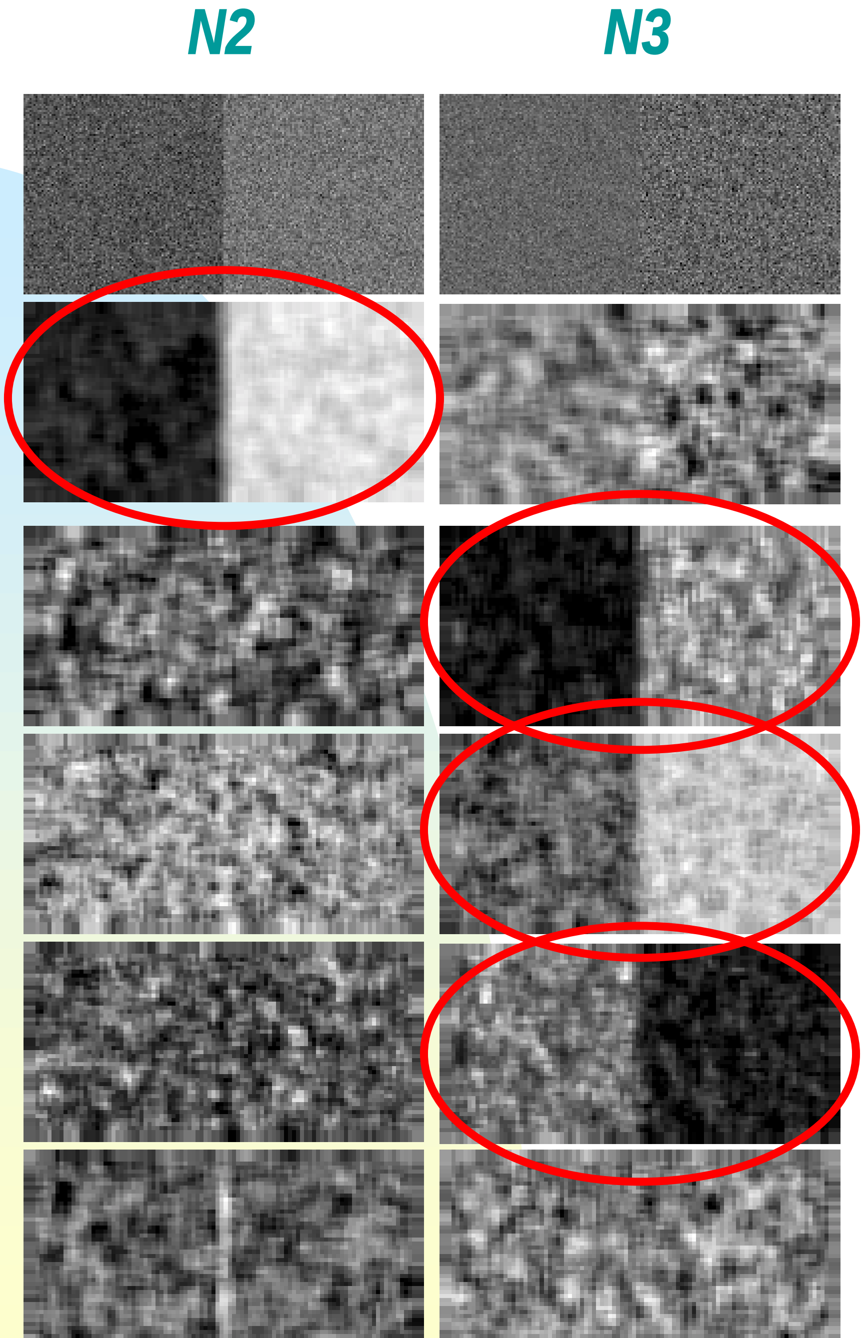


Run-Length Matrix



Gradient Features





Co-occurence matrix

False detection of texture!

Sum Average S(1,0) - S(5,0)

Contrast S(1,0) - S(5,0)

Entropy S(1,0))

Angular Second Moment S(1,0))

Correlation S(1,0))

Image normalization: 1) no normalization

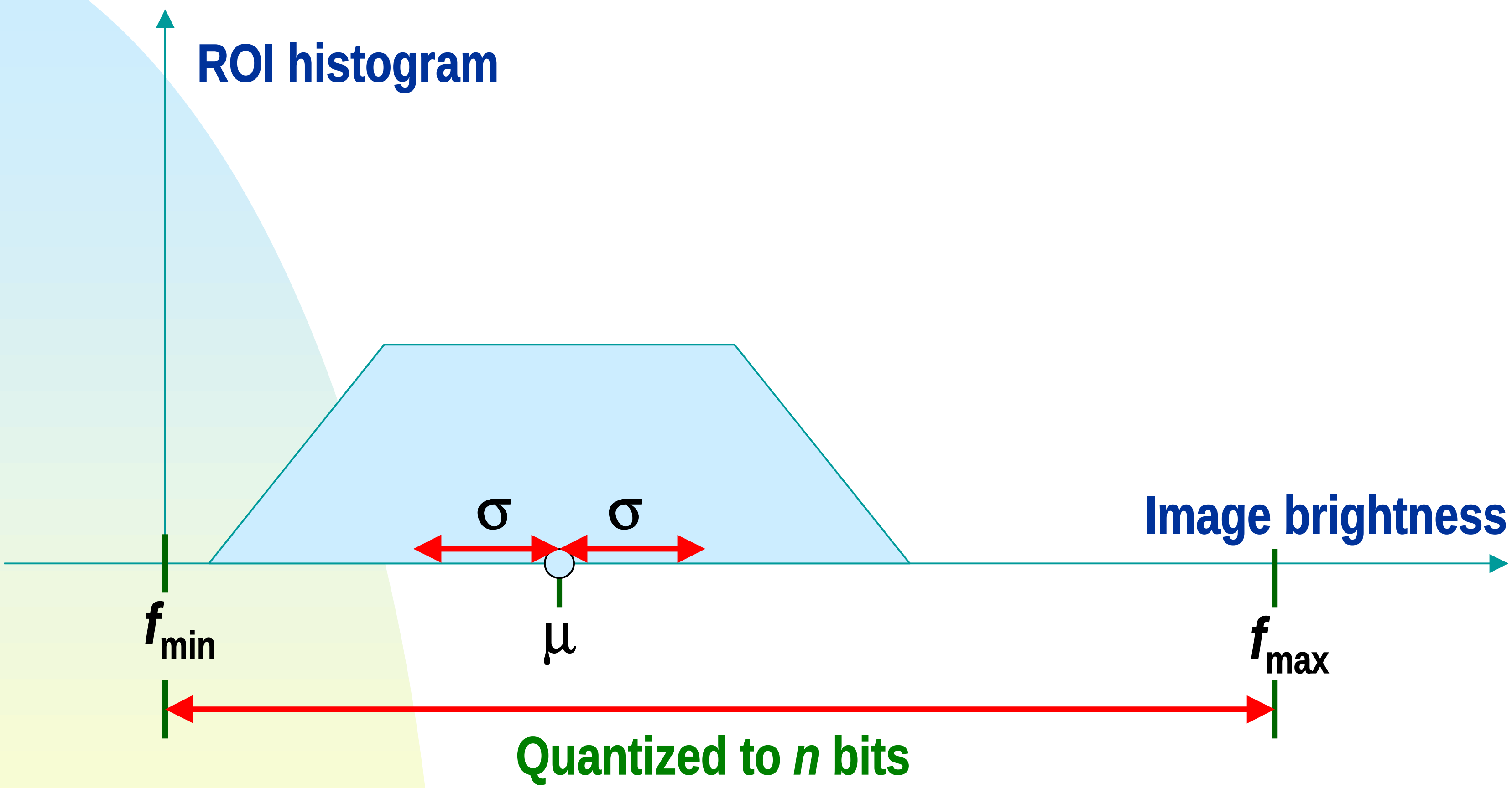


Image normalization: 2) '±3σ' scheme

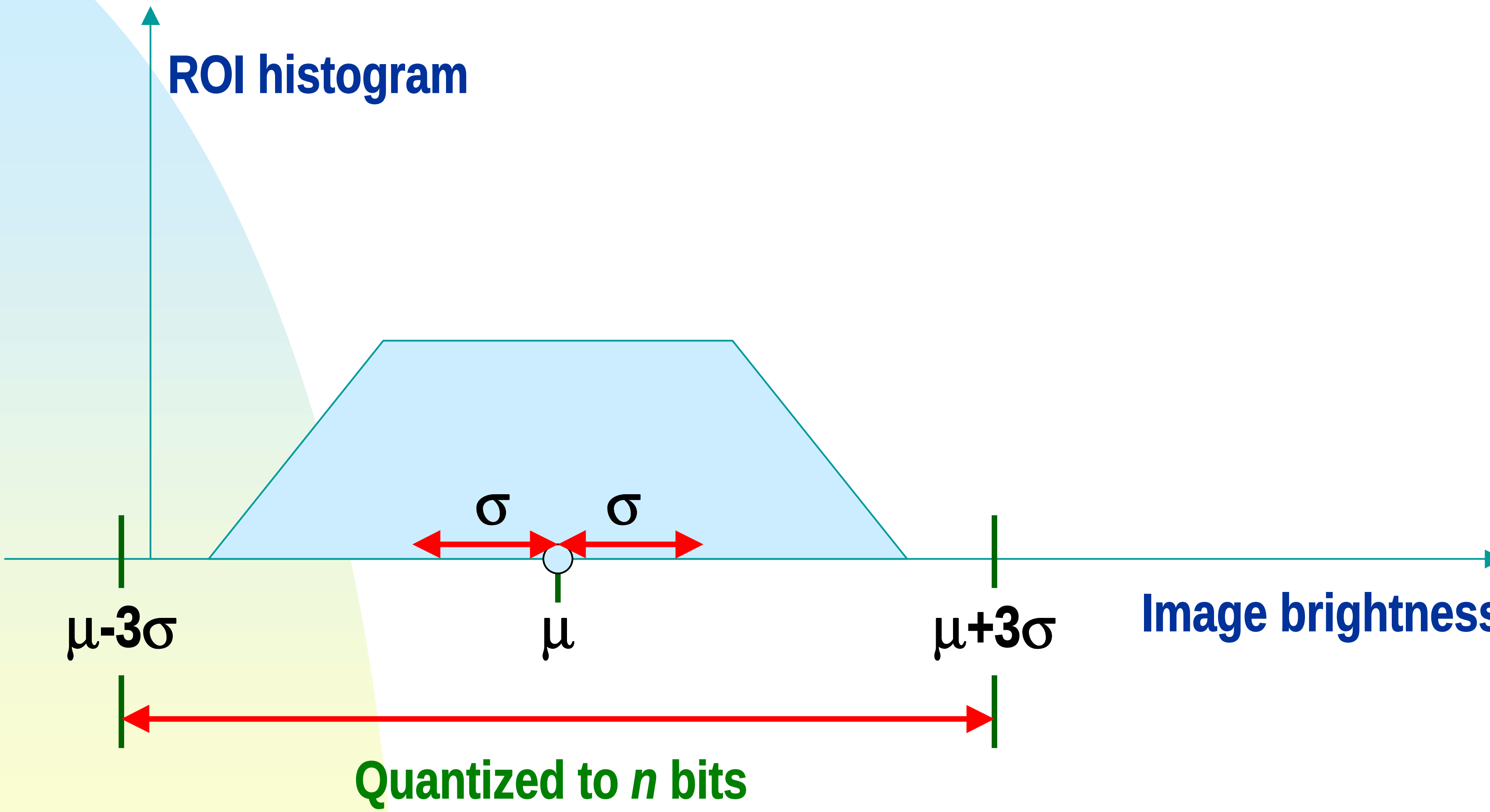
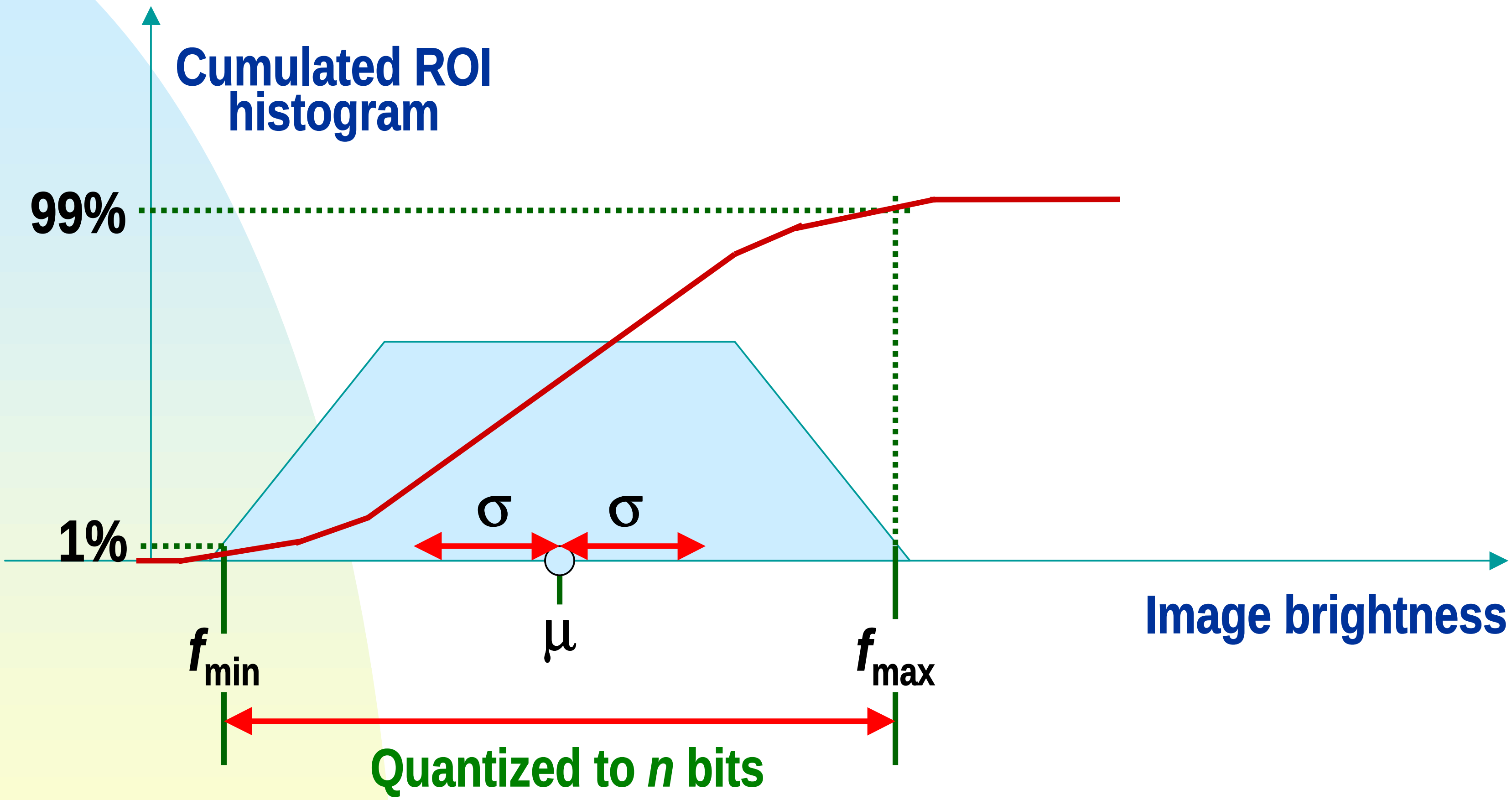
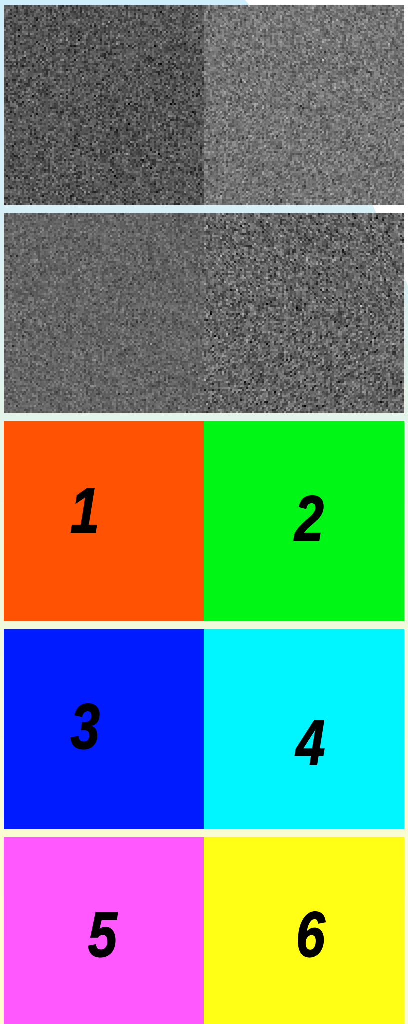


Image normalization: 3) ‘1%-99%’ scheme



Experiment

10 samples per class



N2: m1=85, m2 = 115
s1=s2=20

N3: m1=m2=100
s1=15, s2=25

No normalization

3 sigma

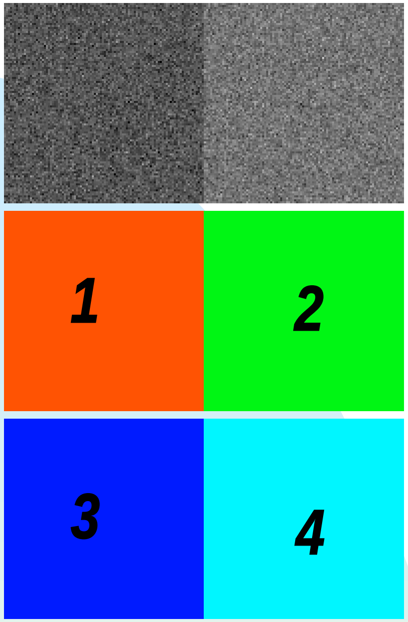
1% - 99%

Co-occurence matrix S(1,0)

Angular Second Moment
Contrast
Sum Of Squares
Inverse Difference Moment
Sum Average
Sum Variance
Sum Entropy
Entropy
Difference Variance
Difference Entropy

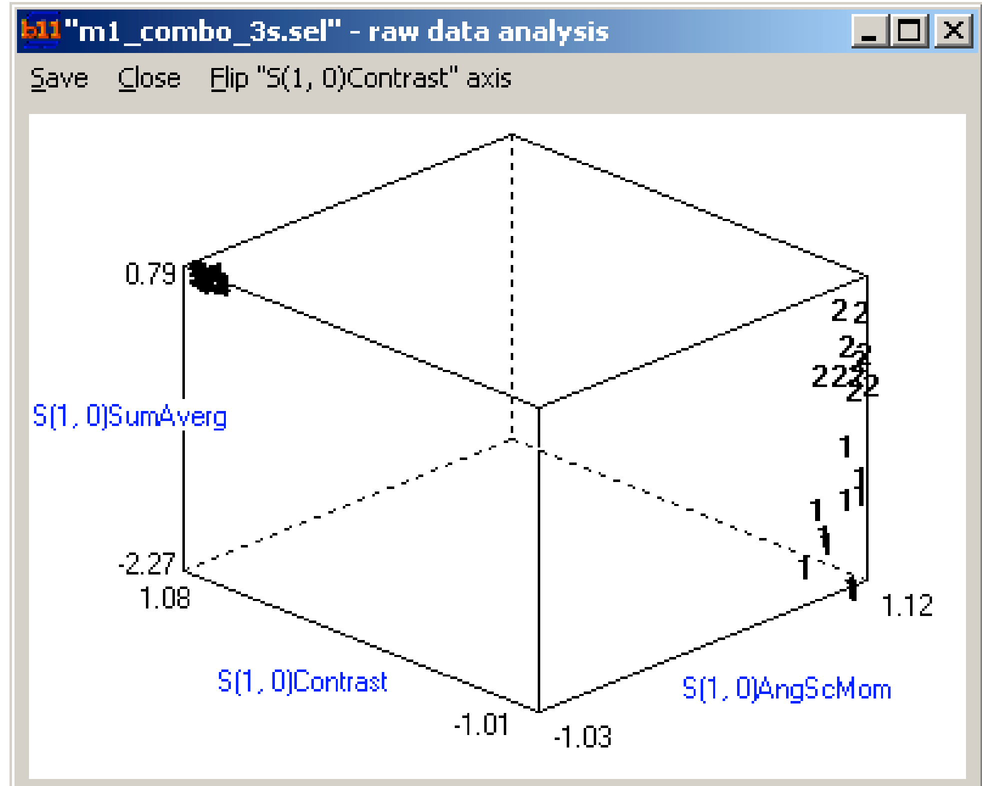
N2

Co-occurence matrix S(1,0)



No normalization

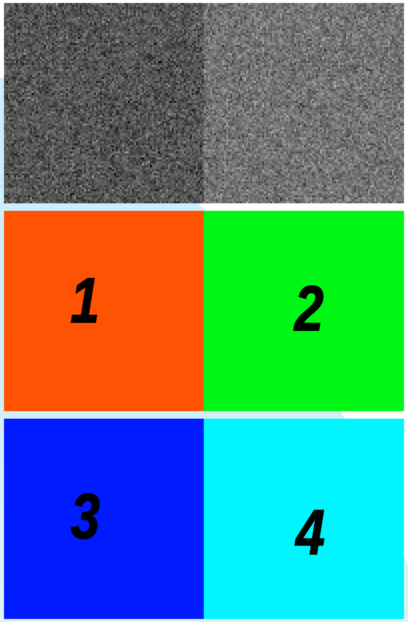
3 sigma



Feature vector standardized: YES
* Results [k-NN classification]
Missclassified data vectors: 10/40 [or 25.00%]
Sample No: 21; Category: 3; ClassResult: 4
Sample No: 22; Category: 4; ClassResult: 3
Sample No: 25; Category: 3; ClassResult: 4
Sample No: 26; Category: 4; ClassResult: 3
Sample No: 27; Category: 3; ClassResult: 4
Sample No: 28; Category: 4; ClassResult: 3
Sample No: 31; Category: 3; ClassResult: 4
Sample No: 36; Category: 4; ClassResult: 3
Sample No: 37; Category: 3; ClassResult: 4
Sample No: 39; Category: 3; ClassResult: 4

In the raw feature space, 3 sigma normalization helps remove the image mean efect.

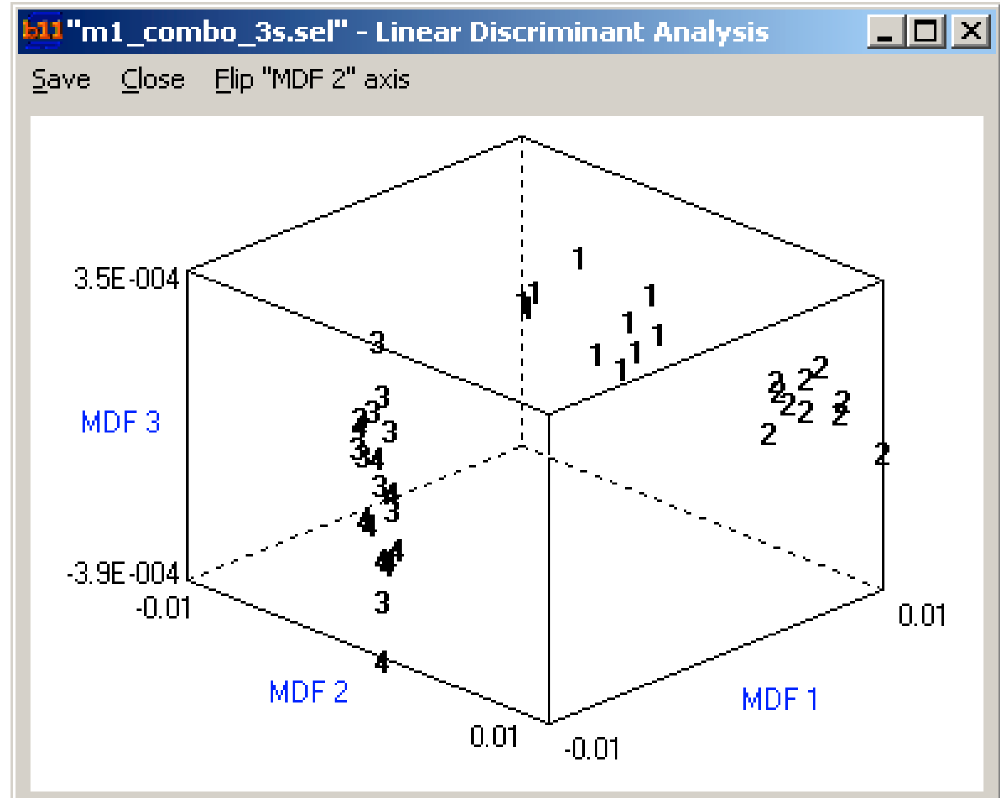
N2



Co-occurence matrix S(1,0) + LDA

No normalization

3 sigma

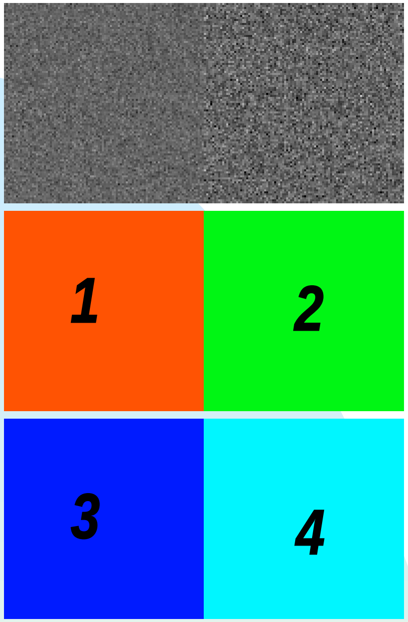


Feature vector standardized: YES
* Results [k-NN classification]
Missclassified data vectors: 8/40 [or 20.00%]
Sample No: 22; Category: 4; ClassResult: 3
Sample No: 26; Category: 4; ClassResult: 3
Sample No: 27; Category: 3; ClassResult: 4
Sample No: 29; Category: 3; ClassResult: 4
Sample No: 33; Category: 3; ClassResult: 4
Sample No: 37; Category: 3; ClassResult: 4
Sample No: 38; Category: 4; ClassResult: 3
Sample No: 40; Category: 4; ClassResult: 3

The spurious classes are not visible in MDF space (LDA does not restore the image mean effect).

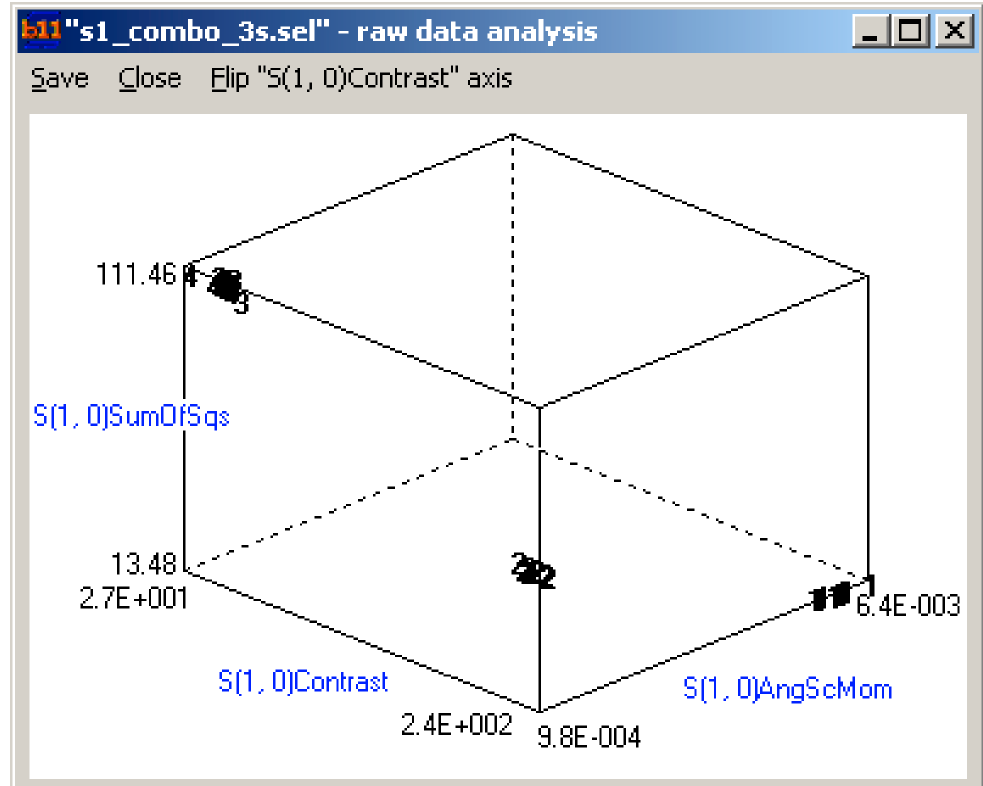
Co-occurence matrix S(1,0)

N3



No normalization

3 sigma

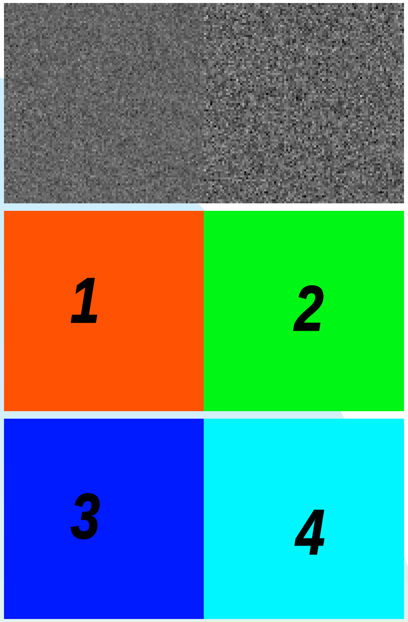


Feature vector standardized: YES
* Results [k-NN classification]
Missclassified data vectors: 11/40 [or 27.50%]
Sample No: 21; Category: 3; ClassResult: 4
Sample No: 23; Category: 3; ClassResult: 4
Sample No: 26; Category: 4; ClassResult: 3
Sample No: 27; Category: 3; ClassResult: 4
Sample No: 28; Category: 4; ClassResult: 3
Sample No: 31; Category: 3; ClassResult: 4
Sample No: 32; Category: 4; ClassResult: 3
Sample No: 34; Category: 4; ClassResult: 3
Sample No: 35; Category: 3; ClassResult: 4
Sample No: 36; Category: 4; ClassResult: 3
Sample No: 40; Category: 4; ClassResult: 3

In the raw feature space, 3 sigma normalization helps remove the image variance efect.

N3

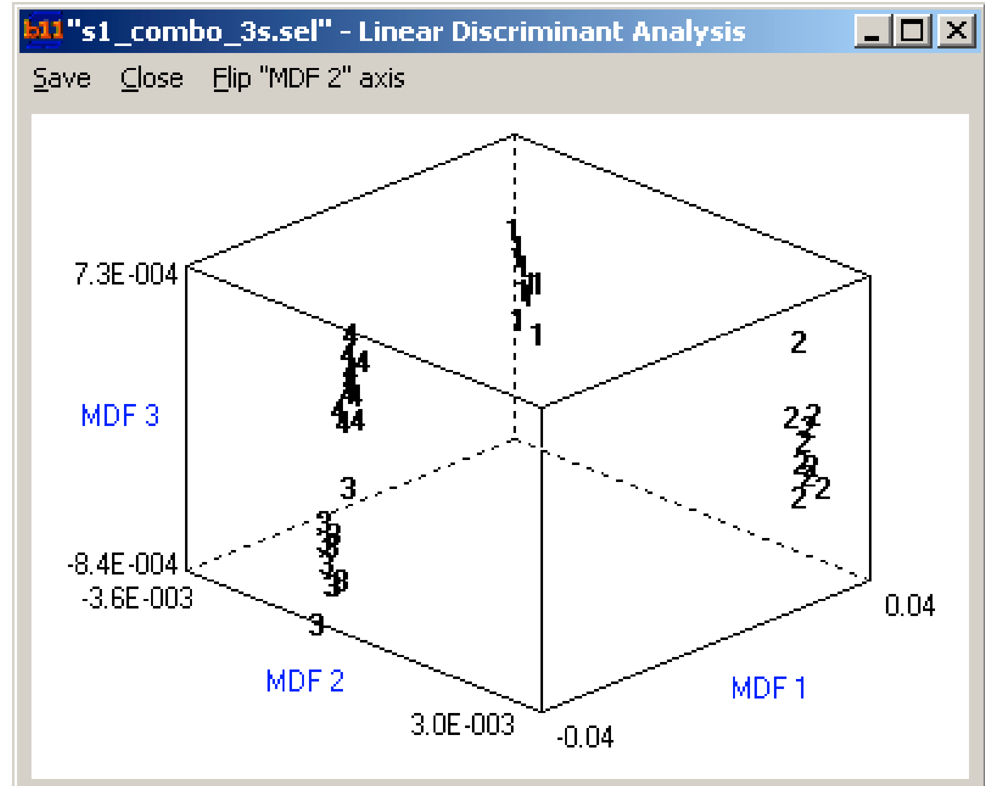
Co-occurence matrix S(1,0) + LDA



No normalization

3 sigma

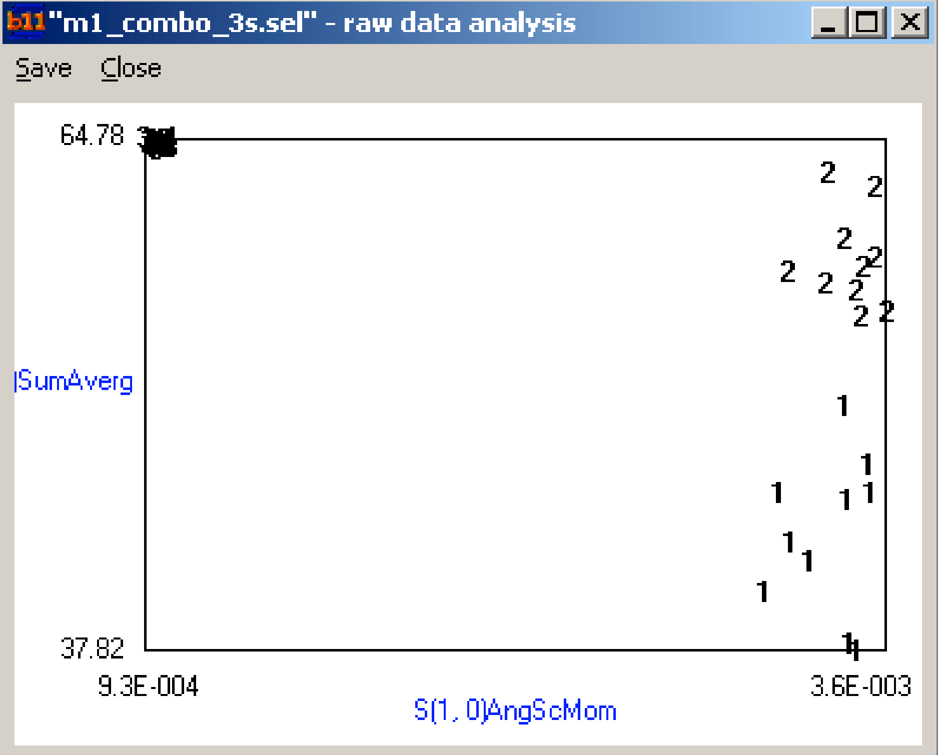
* Results [k-NN classification]
Missclassified data vectors: 0/40 [or 0.00%]

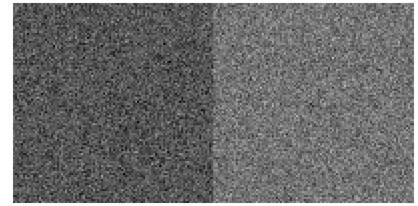


Still, it is possible to separate classes based on higher-order features - even if they actually differ only by variance (spurious effect).

Hopefully, instrinsic texture properties may mask this effect

Co-occurence matrix S(1,0)



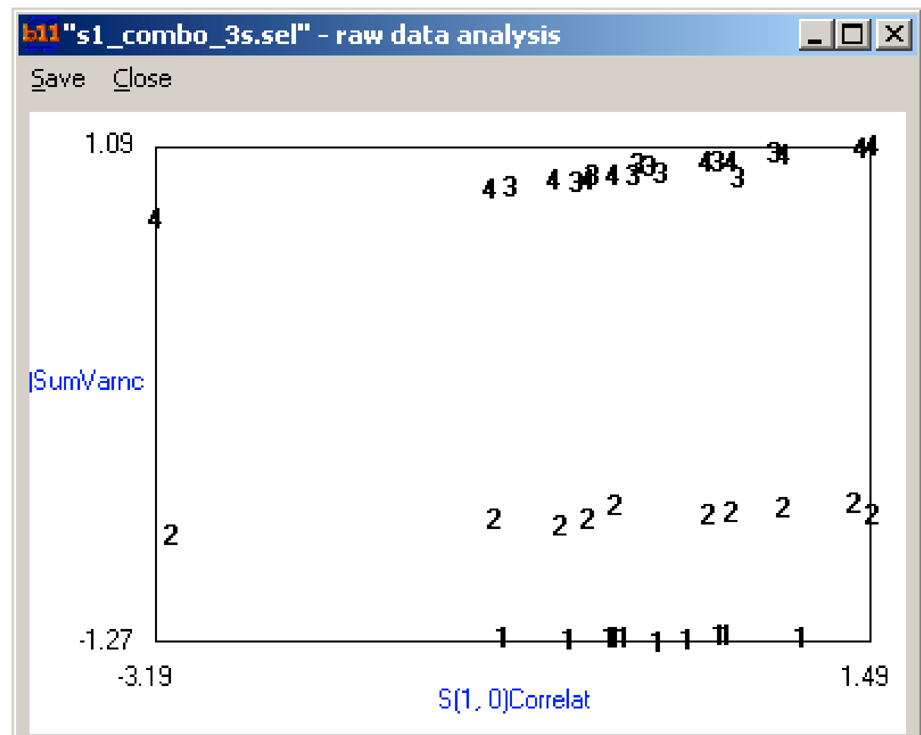


N2

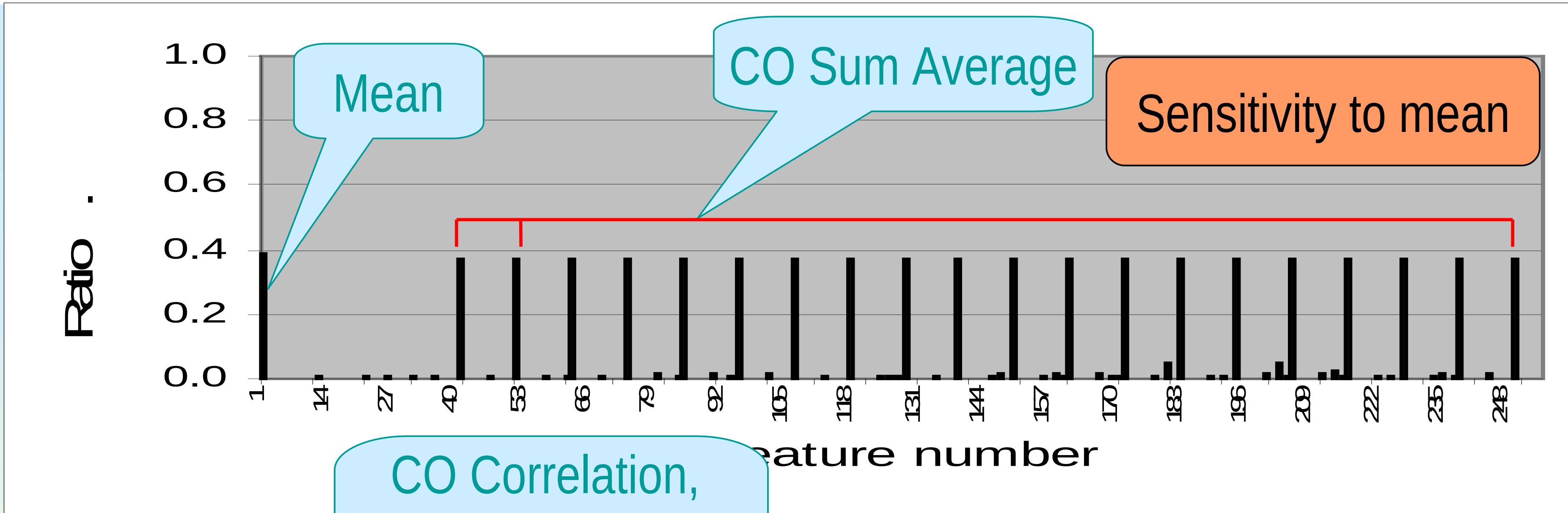
Sum Average is sensitive to image mean

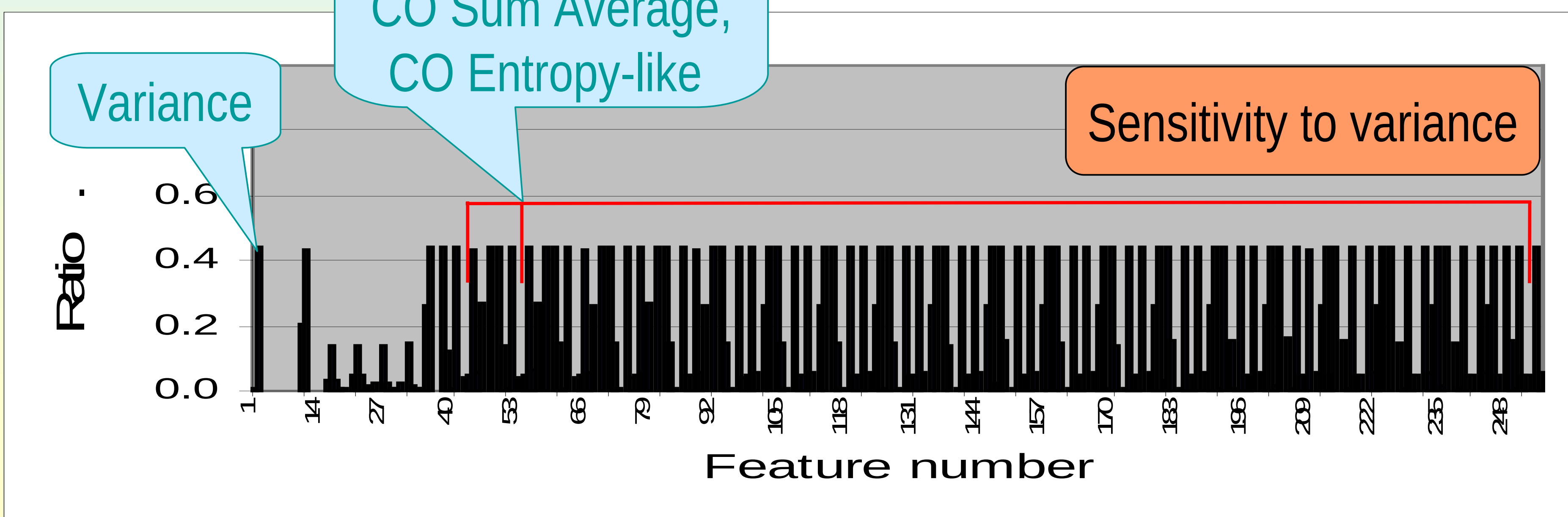
N3

Image variance does not affect Correlation.



Feature properties



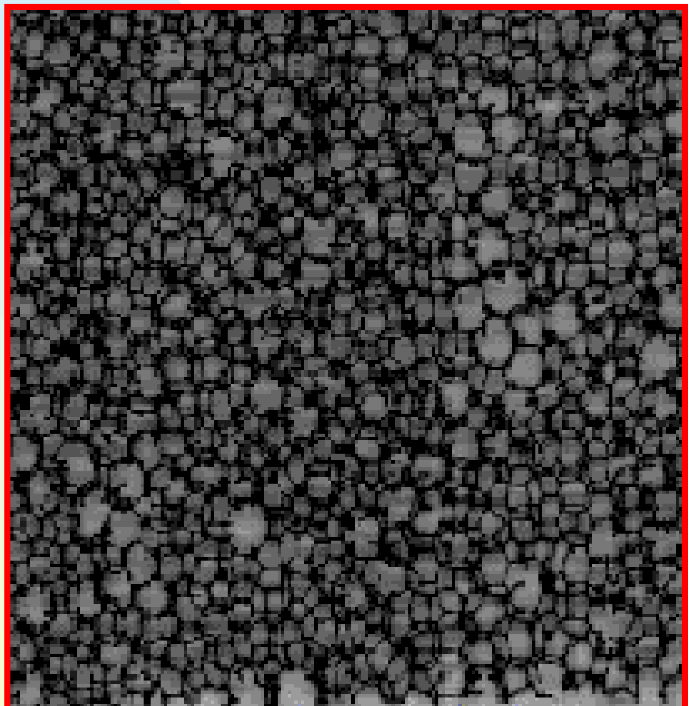


Conclusion

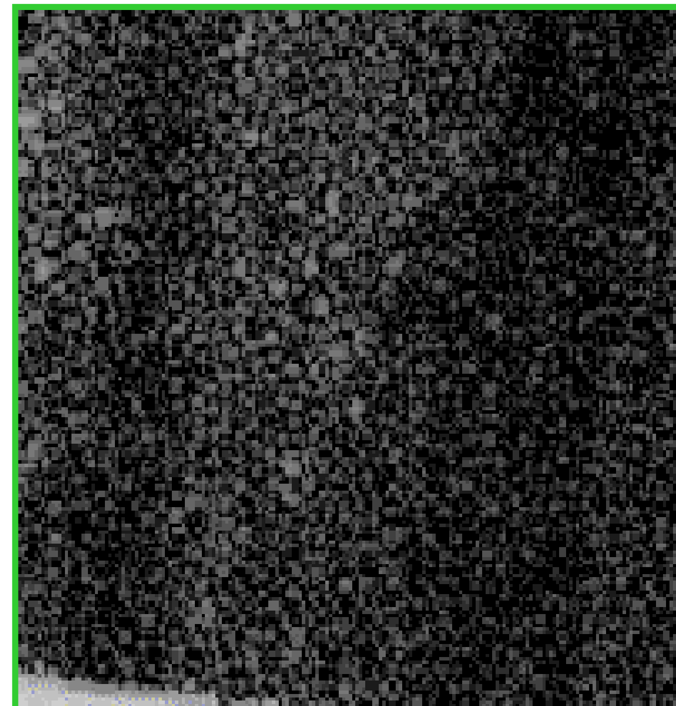
- Both ROI mean and ROI variance affect significantly higher order features, leading to spurious texture detection.
- Image normalization is necessary prior to parameter computation to reduce this effect.
- Further study is needed to find texture features that are truly independent on image first-order parameters.

Experiment: optical images

- reticulated foam of different porosity
  (2 texture classes)



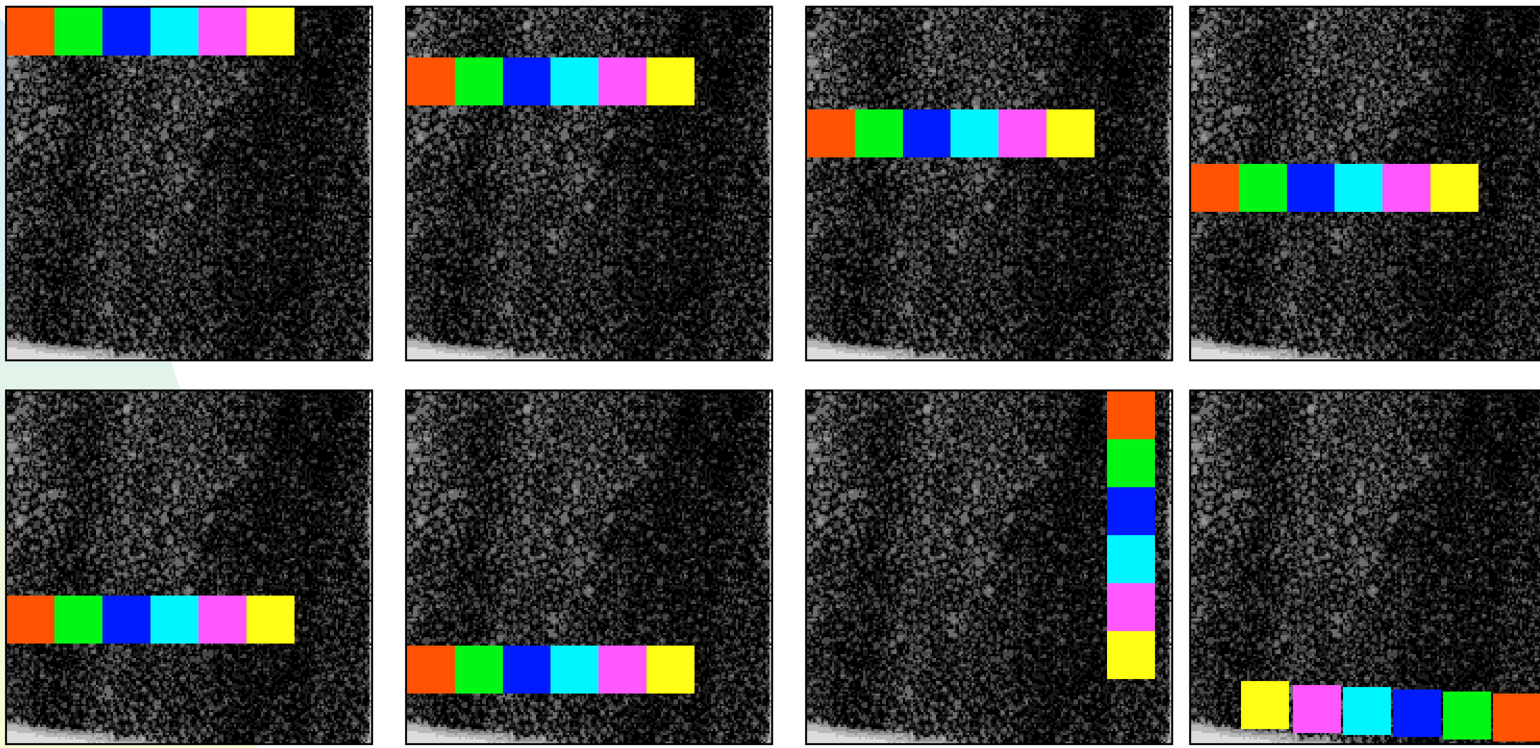
Foam 1
(large pore size)



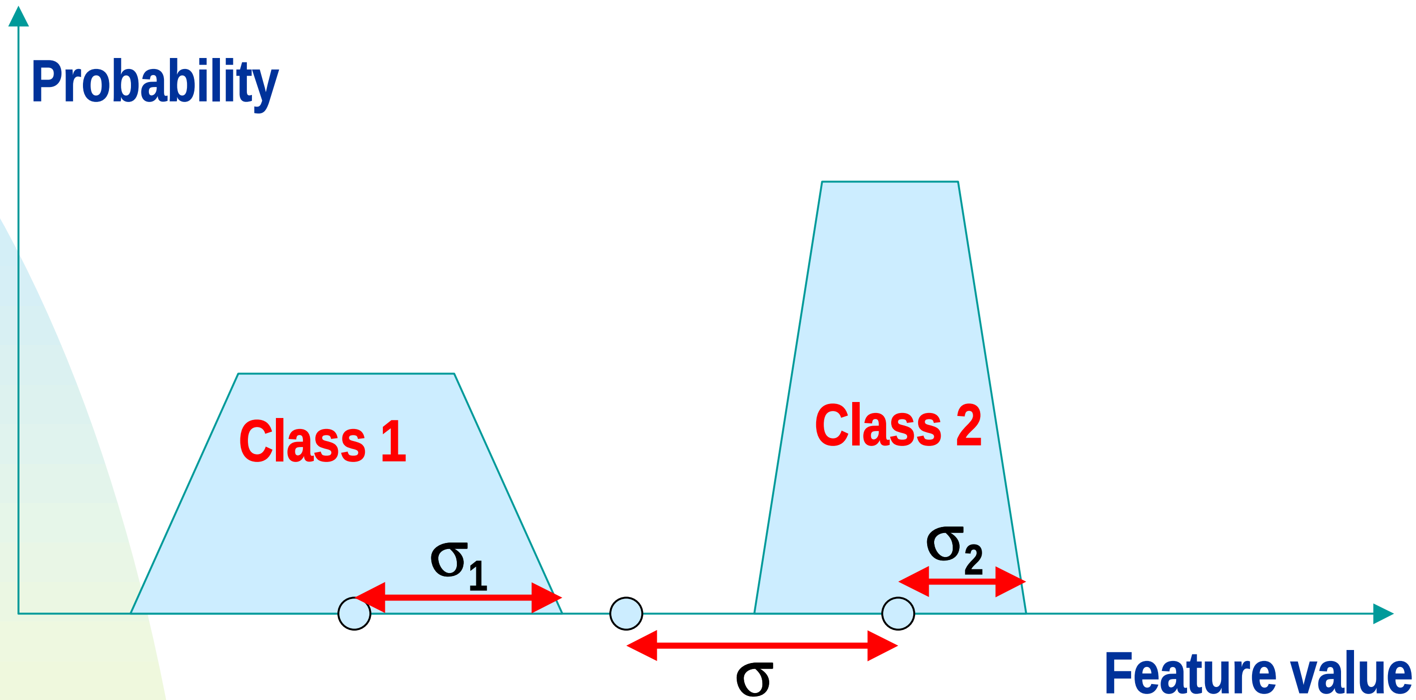
Foam 2
(small pore size)

Methods

- computation of texture statistical parameters (48 ROI, each 23×23 pixels)



Methods: texture class separation criterion



$$F = \frac{D}{V} = \frac{\sigma^2}{0.5(\sigma_1^2 + \sigma_2^2)}$$

Ratio of between-classes to within-classes variance.

Effect of ±3σ normalization

- Since μ and σ^2 are both constant [with regard to the (f_{max}–f_{min}) window], their effect on features disappears.
- Features that are masked by μ and σ^2 variation regain their ability to discriminate texture classes.
- Features that did not possess relevance to texture classes do not produce significant values of *F* anymore.