Use of open source in development of algorithms for multivariate analysis of texture images

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Andreas Flø
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Introduction

- Image Texture and methods
- Open source software
  - ImageJ
  - The UMB texture toolkit
  - Frost damage classification of brick walls

Members of imaging group

Ole Mathis Opstad Kruse

This is the imaging group at IMT

Illustration Ole Mathis Opstad Kruse

Knut Kvaal
Associate Professor

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Andreas Flø
Engineer, PhD student
Hyperspectral imaging

Jack Zeigler
Associate Professor

Arne Grimenes
Associate Professor

Stein Ivar Øvergaard
PhD student
Precision agriculture

Ole Mathis Kruse
PhD student
Imaging plant stress

Imaging techniques can be used in many fields to characterise temporal as well as spatial changes in a system

For example, in plant science, imaging in different wavelength regions can be used to study important processes such as photosynthesis, pigment induction, leaf temperature regulation and transpiration. In the food sciences, image analysis is a very important part of process optimalization and in industrial production plants. In agriculture, image analysis is combined with Near Infrared Spectroscopy (NIRS) to monitor and estimate production in the field.

Extracting relevant and quantitative information from the many images generated during an experiment requires application of suitable image processing and analysis techniques. We use many different techniques such as textural image analysis, multivariate image analysis (MIA) and particle image velocimetry (PIV). We also develop methods and algorithms for texture analysis.

Applications
Biophysics
Food sciences
Agriculture
Materials
Meteorology

Current projects
Imaging plant stress
Imaging plant roots
Image texure features
Hyperspectral imaging
Artifical photosynthesis

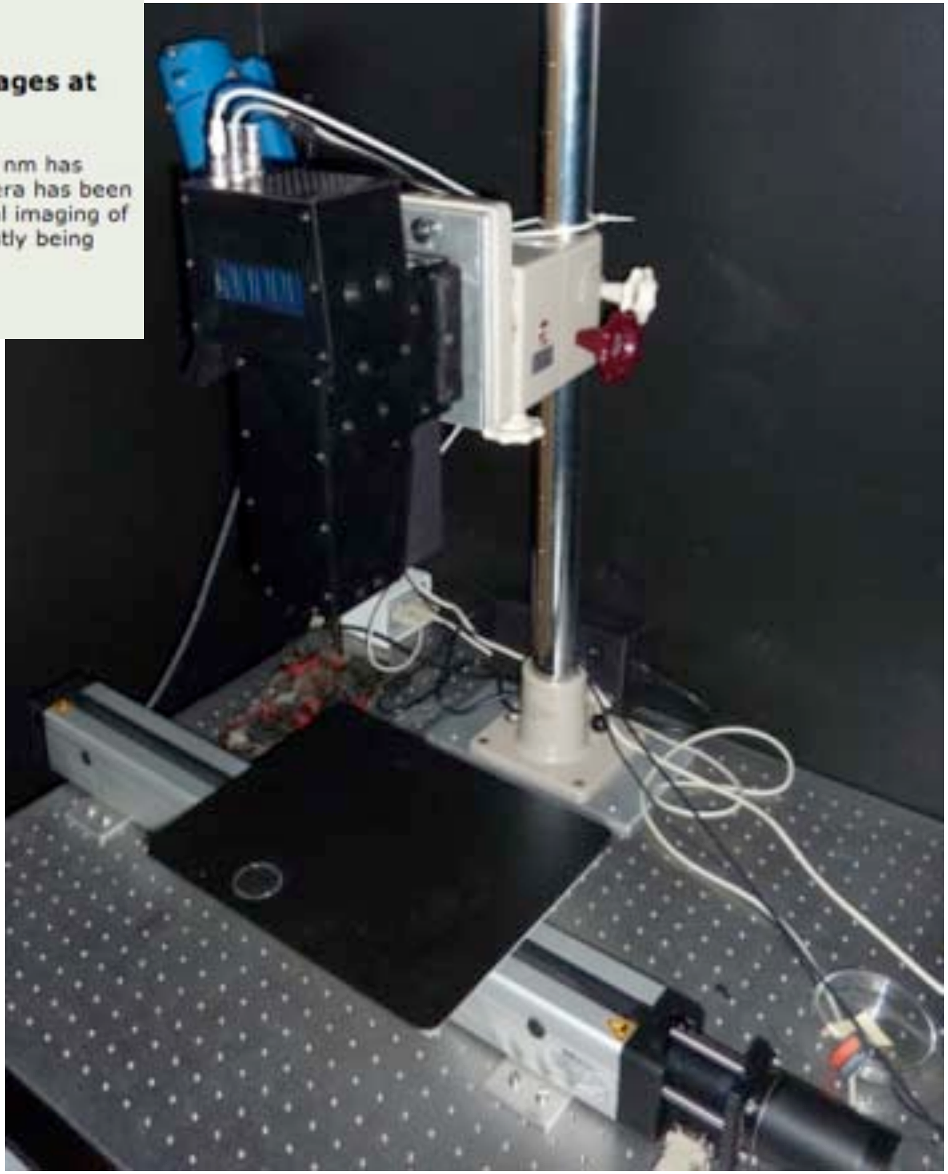
Hyperspectral imaging

Ole Mathis Opstad Kruse

A hyperspectral camera can be used to capture images at several different wavelenghts

A hyperspectral camera with a spectral range of 900 nm – 1700 nm has recently been installed in the Visualisation Laboratory. The camera has been tested in several preliminary experiments, such as hyperspectral imaging of healthy and ozone damaged leaves. Several projects are currently being initiated.

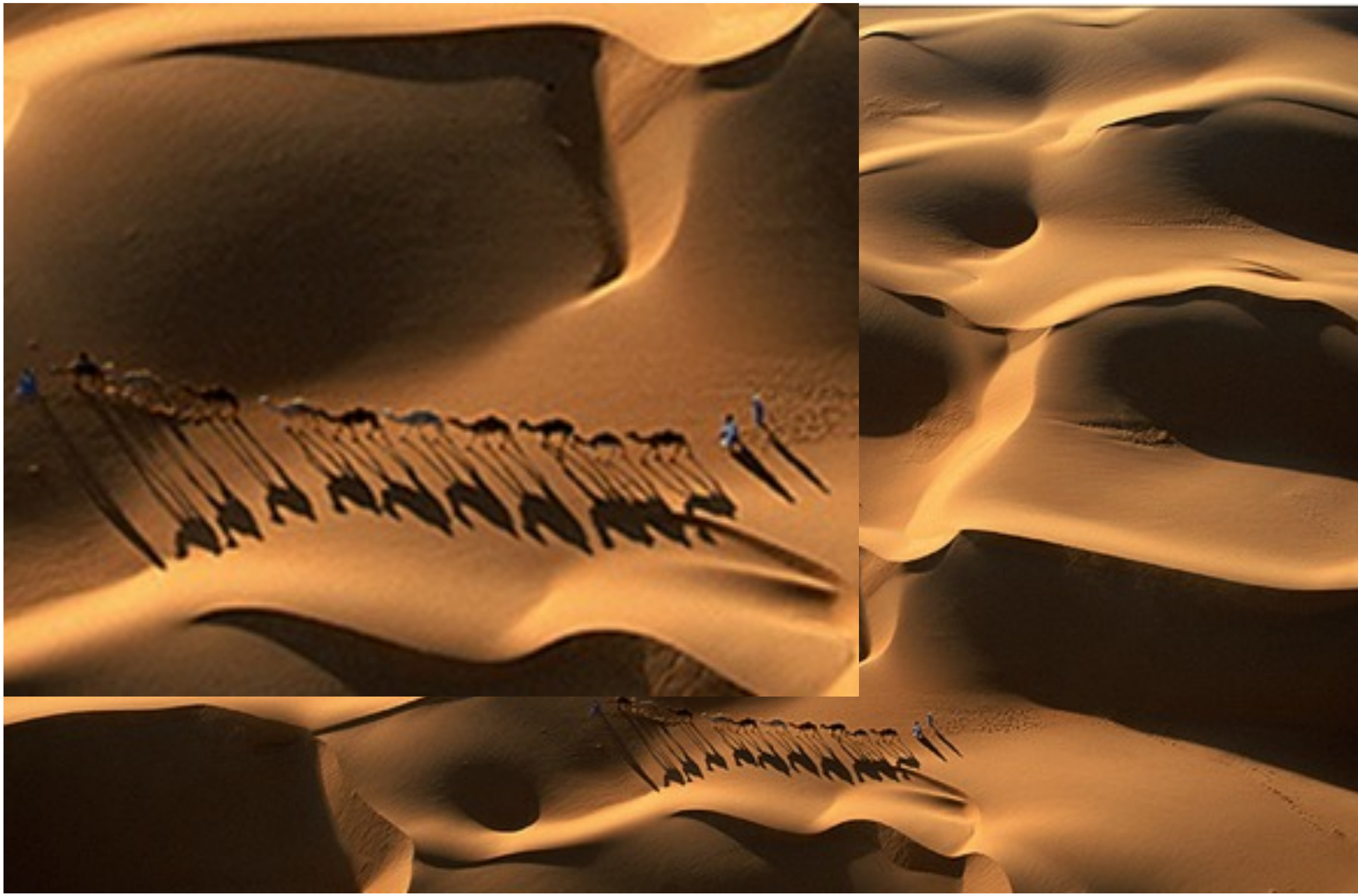
Contact: Andreas Flø (andreas.flo@umb.no)



Texture - A matter of scale..

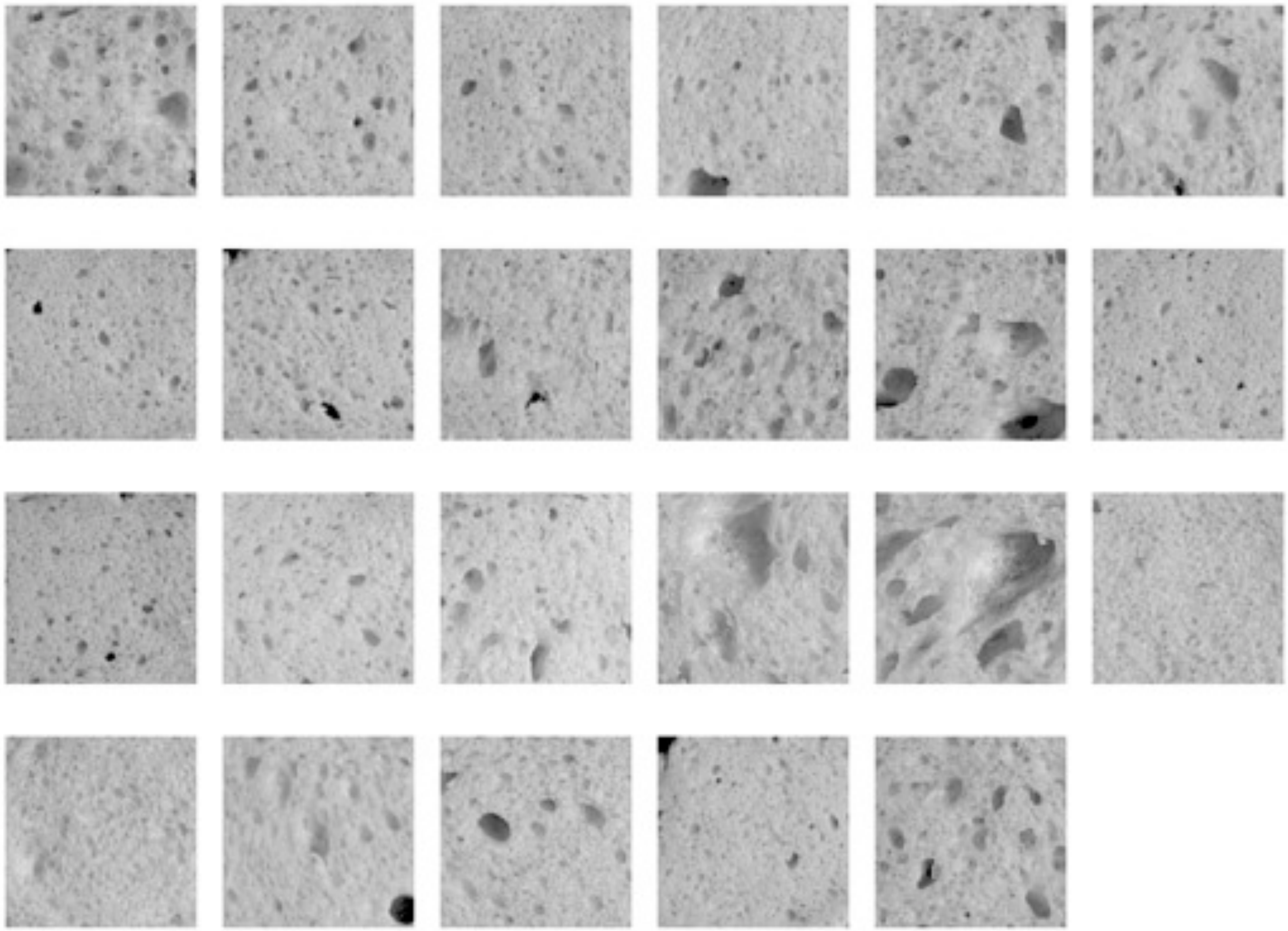
Yann Arthus-Bertrand

Texture - A matter of scale..



Yann Arthus-Bertrand

Texture - A matter of scale and illumination



Texture - A matter of scale and illumination

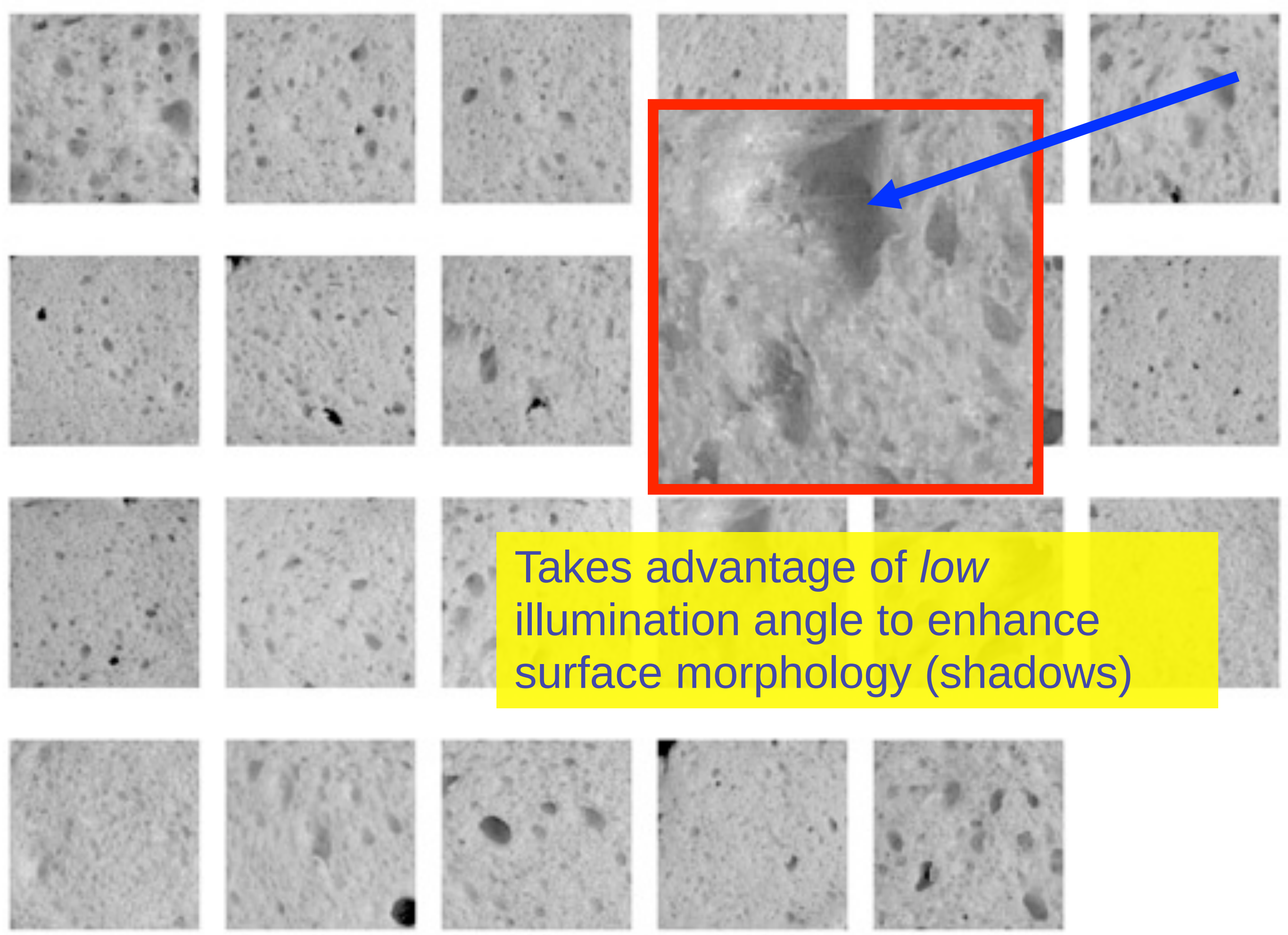
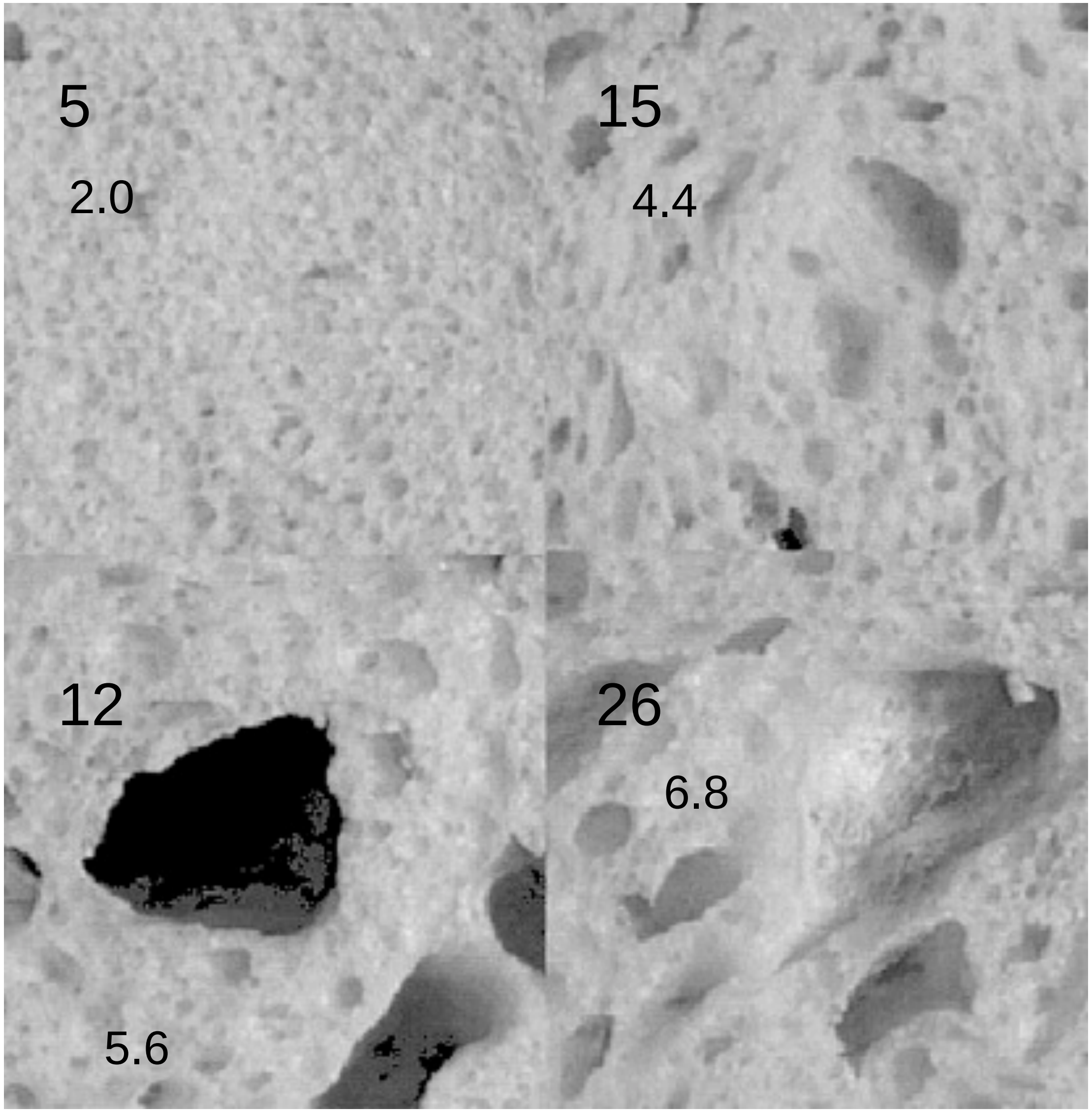


Image Texture and Methods

- Texture may be described as a pattern that is spatially repeated, either deterministically or stochastically.
- In the present context, texture is classified in a continuum – from completely isotropic (displaying no preferred orientation) to strongly anisotropic (images with strong structure).
- A facade stone (e.g. granite) could serve as an isotropic illustration while a texture comprised of brick layers (e.g. sandstone, schist) is strongly anisotropic.



Selected images of four samples with different degree of ”Sensory porosity” (Ref: Dalman porosity table)

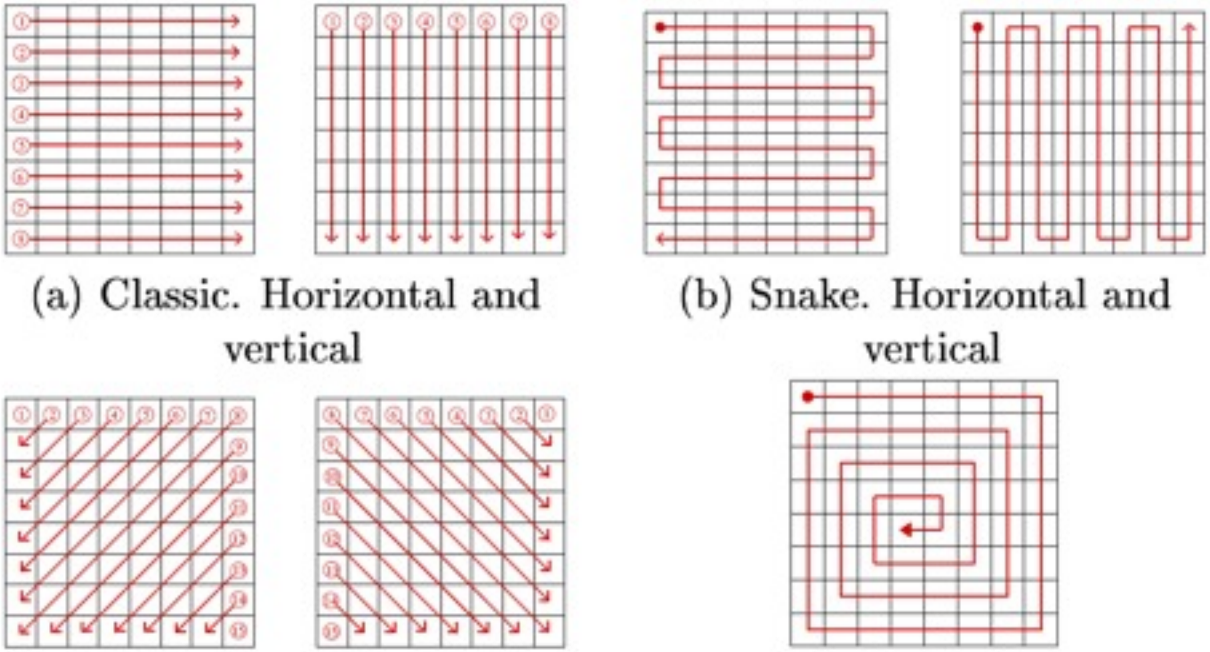
”Feature detector”

- A mathematical method to describe properties hidden in images of the objects in scope
  - A number, a vector
- Examples:
  - Sensory porosity
  - A baking process

Angle Measure Technique

- The angle measure technique, AMT, is a powerful tool for analysis of one- and two-dimensional isotropic signals. Developed in 1994 by Robert Andrle for description of complex geomorphic lines, it was later introduced into chemometrics as a general approach for textural analysis of generic 'measurement series.
- The most important AMT information is the mean angle spectrum (MA) (or median angle) that reflects signal complexity on all possible scales simultaneously.

AMT – Angle Measure Technique – “Crash intro”



(a) Classic. Horizontal and vertical

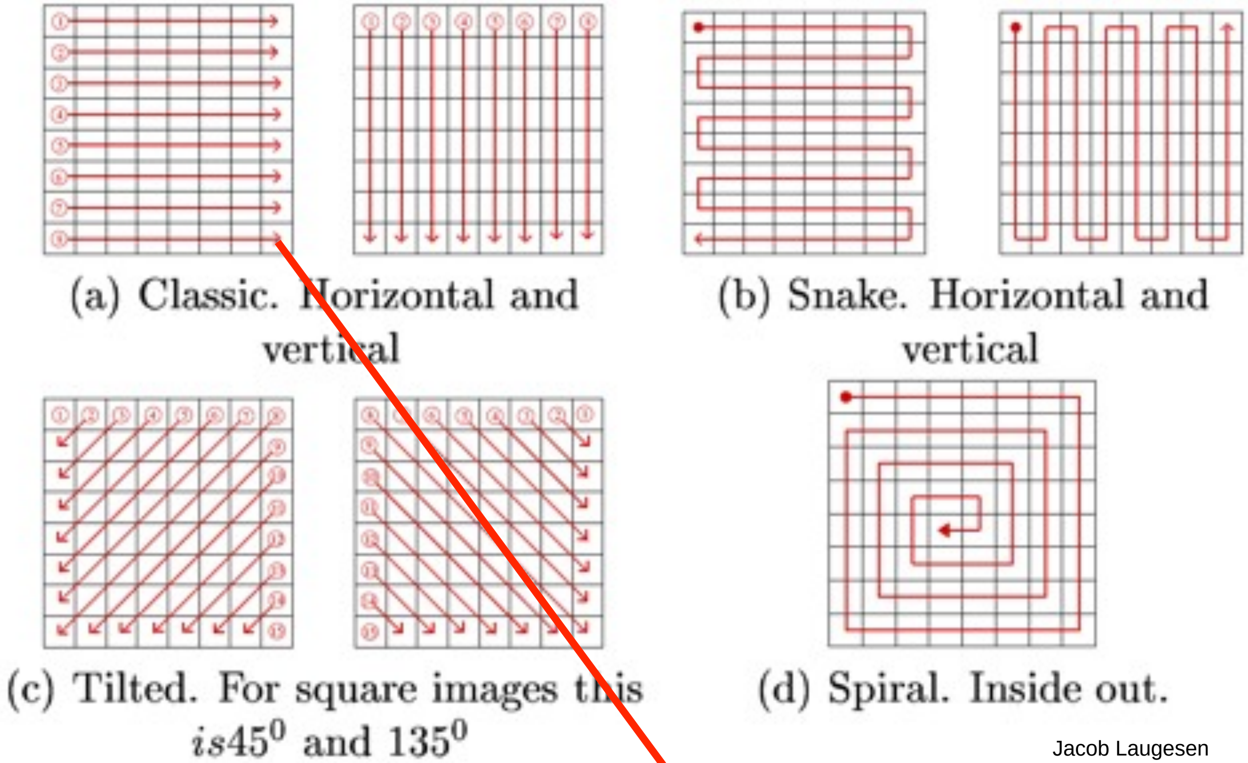
(b) Snake. Horizontal and vertical

(c) Tilted. For square images this $is 45^0$ and 135^0

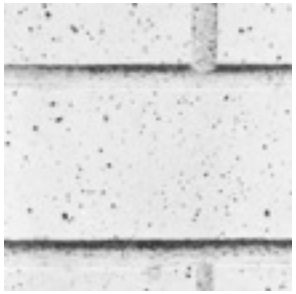
(d) Spiral. Inside out.

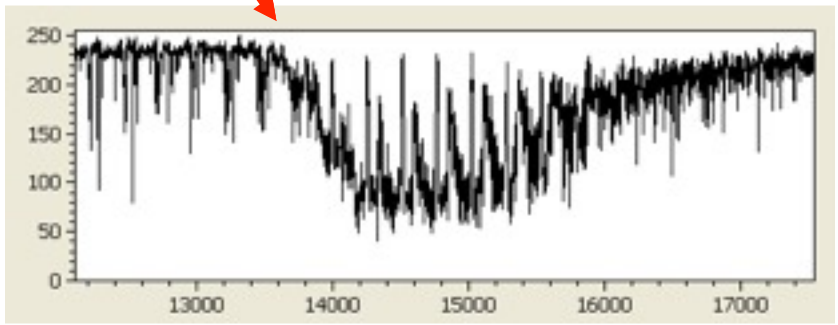
Jacob Laugesen

Vectorise an image cont.

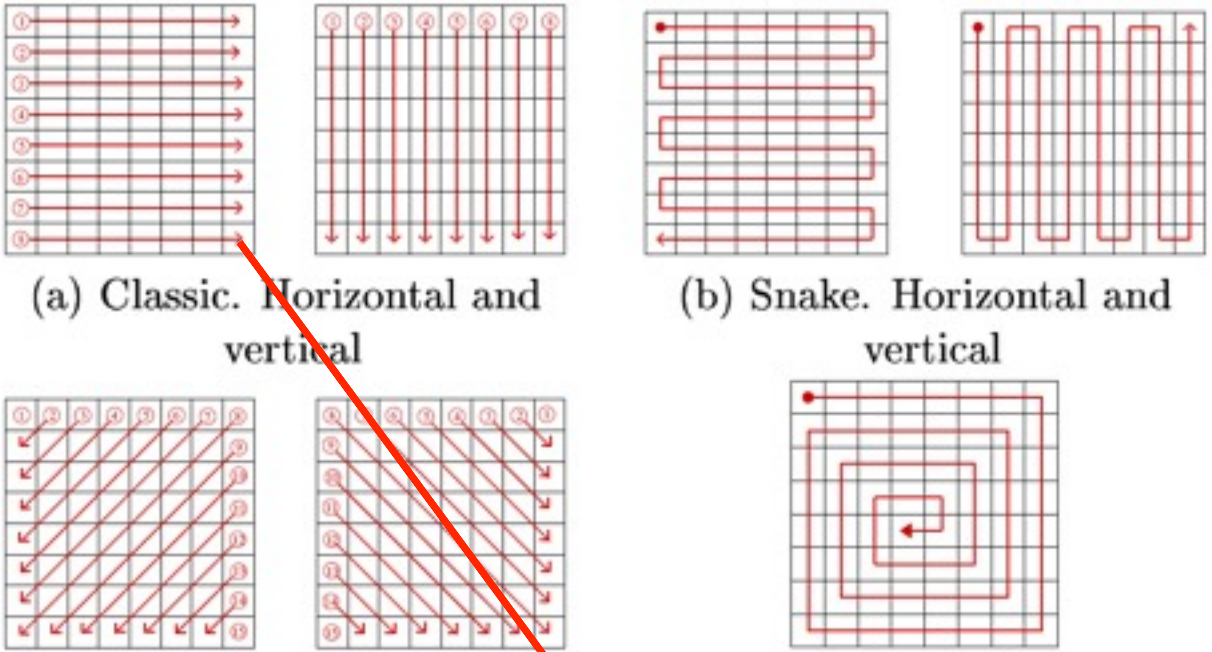


Jacob Laugesen





Vectorise an image cont



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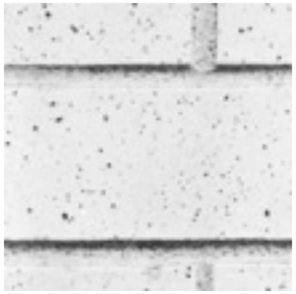
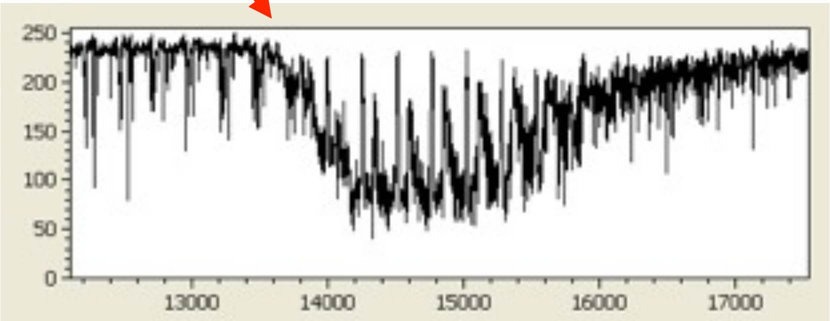
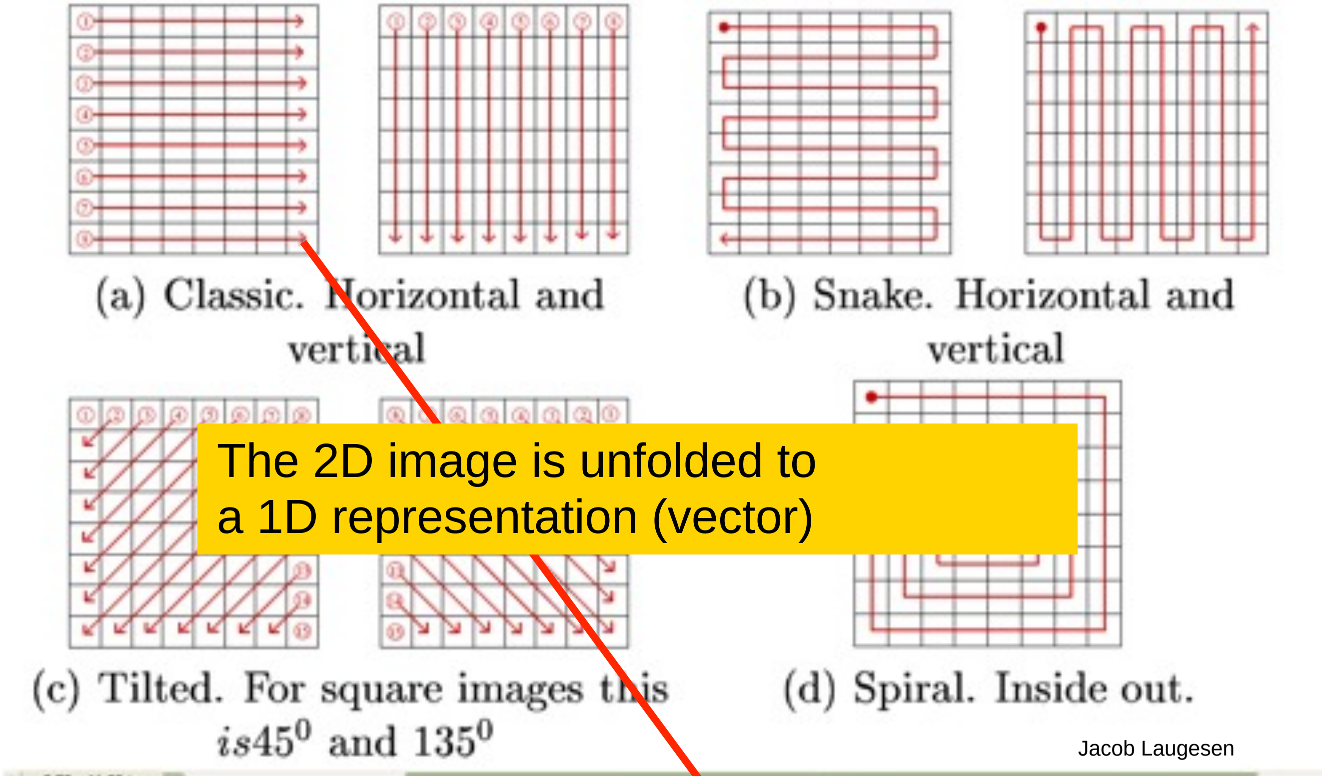
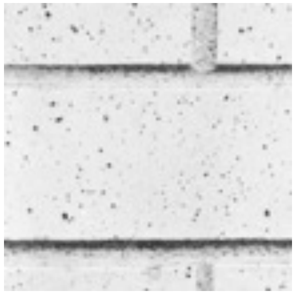


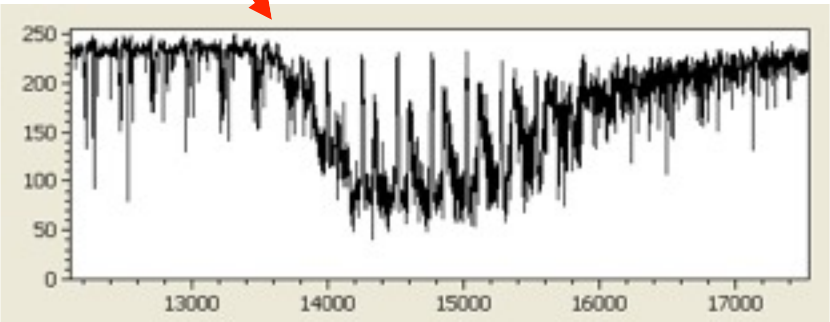


Vectorise an image cont

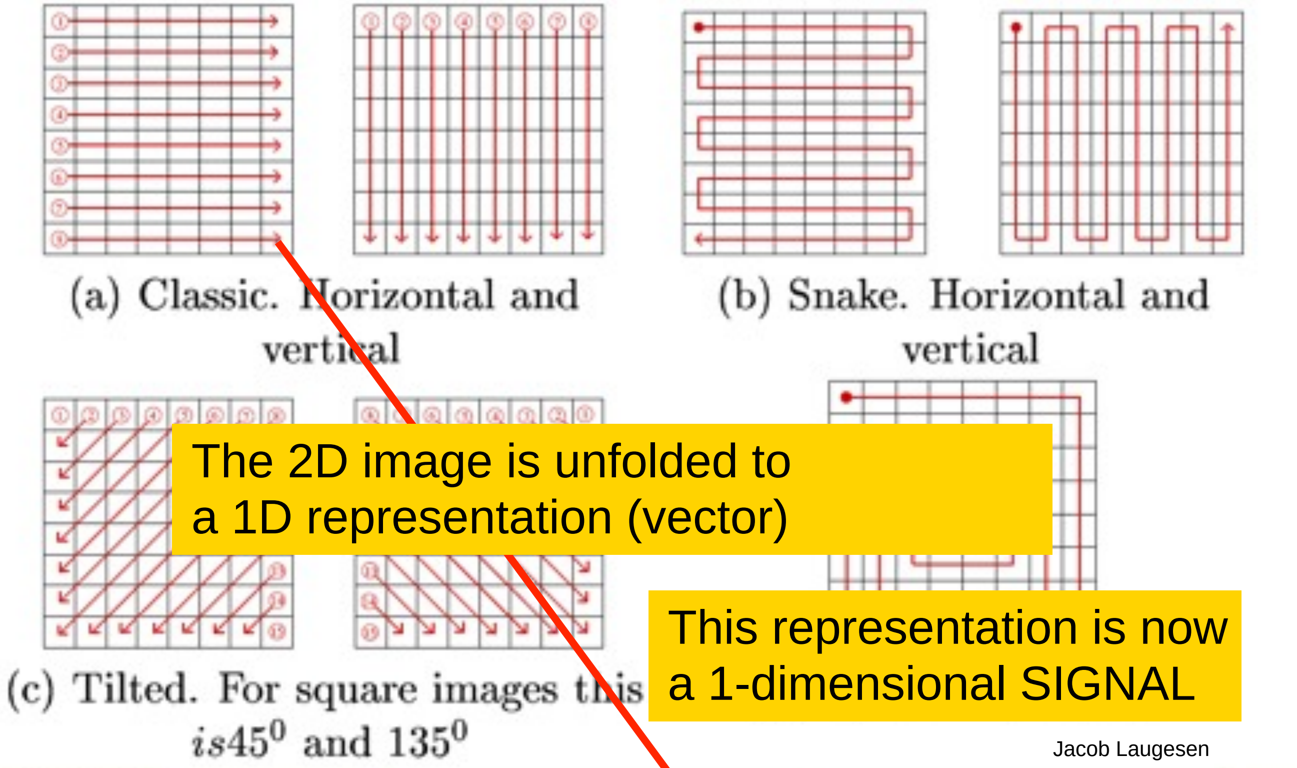


The 2D image is unfolded to a 1D representation (vector)





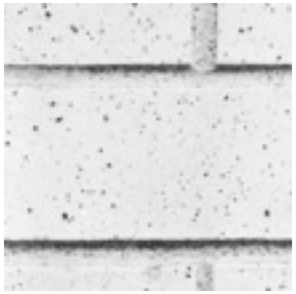
Vectorise an image cont

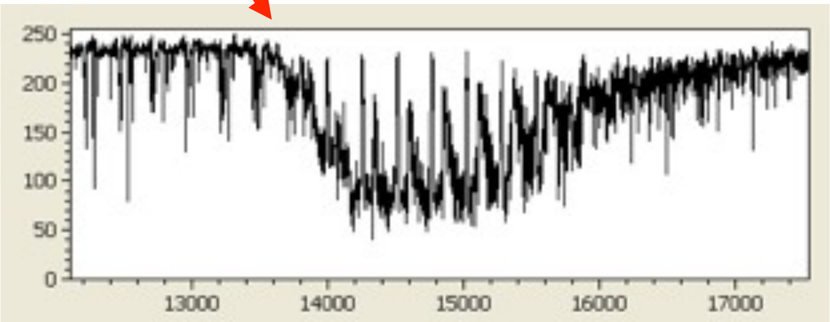


The 2D image is unfolded to a 1D representation (vector)

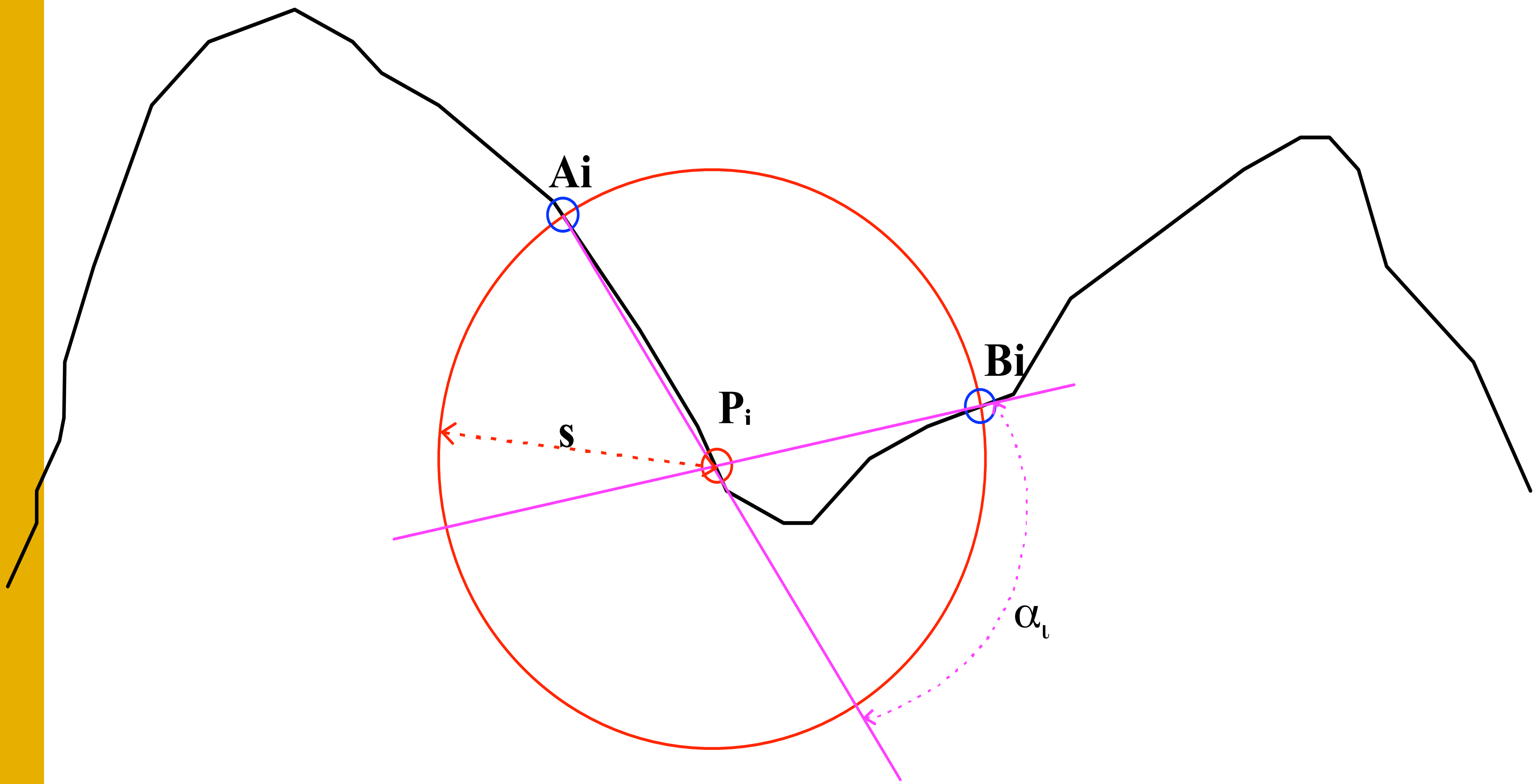
This representation is now a 1-dimensional SIGNAL

Jacob Laugesen



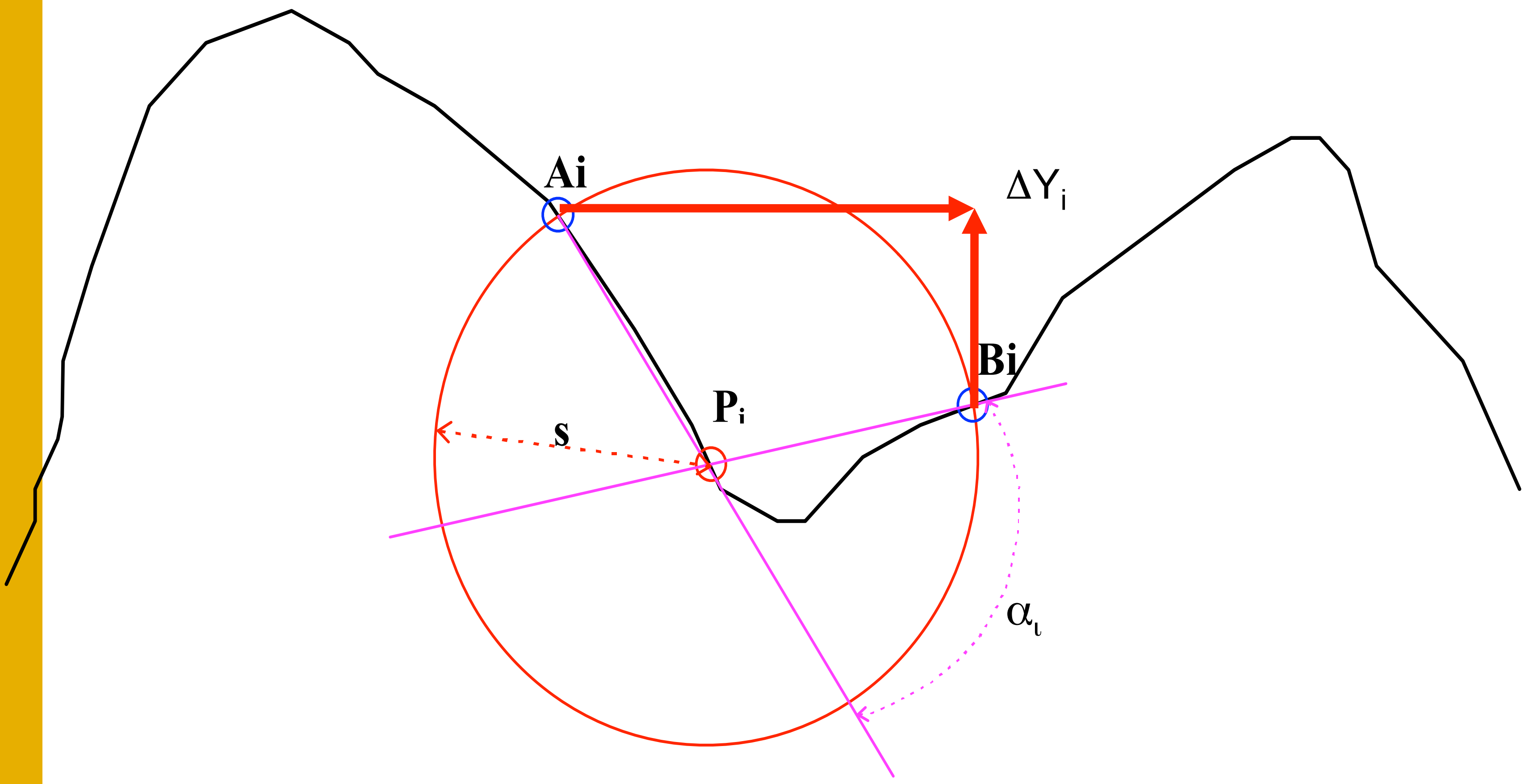


Angle Measure Technique (AMT)



$$\alpha(s) = 1/M * \Sigma_{i=1,M} (\alpha_i)_s$$

Angle Measure Technique (AMT)



$$\alpha(s) = 1/M * \Sigma_{i=1,M} (\alpha_i)_s$$

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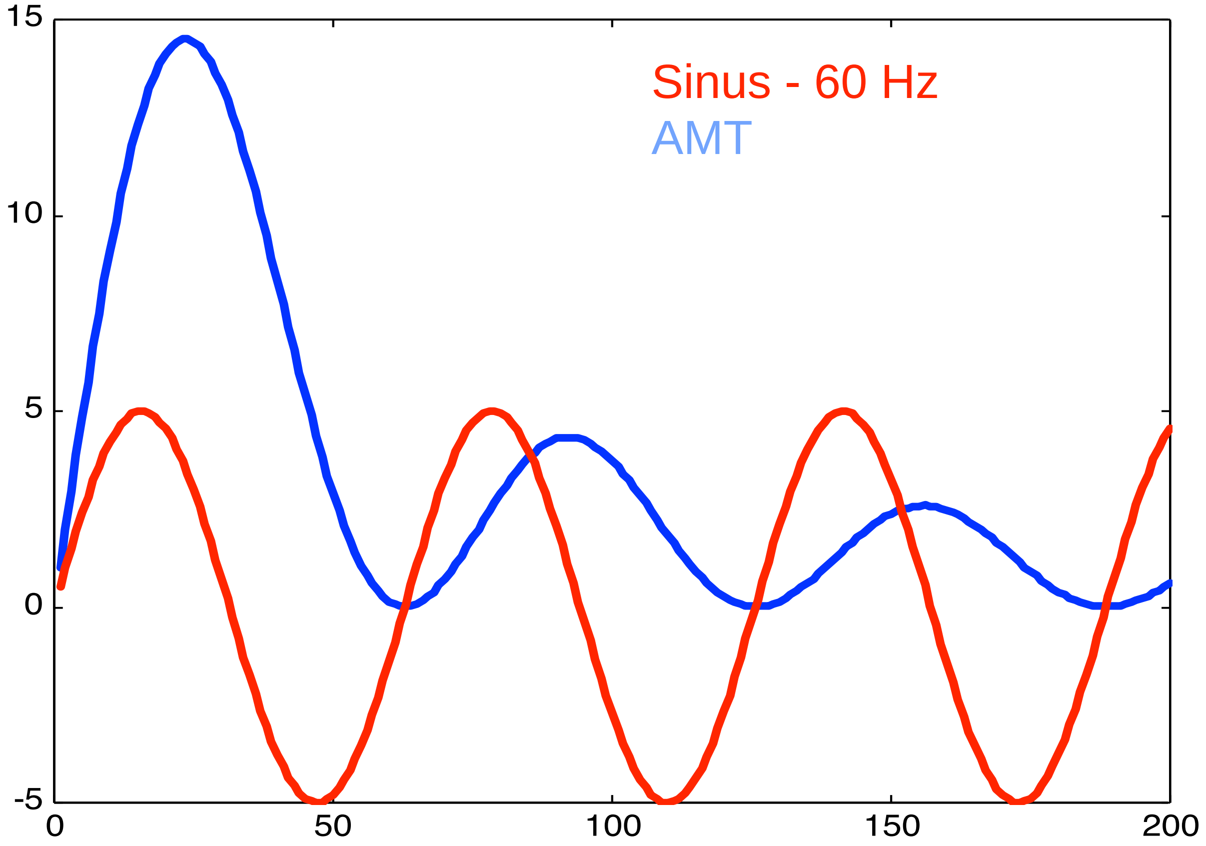
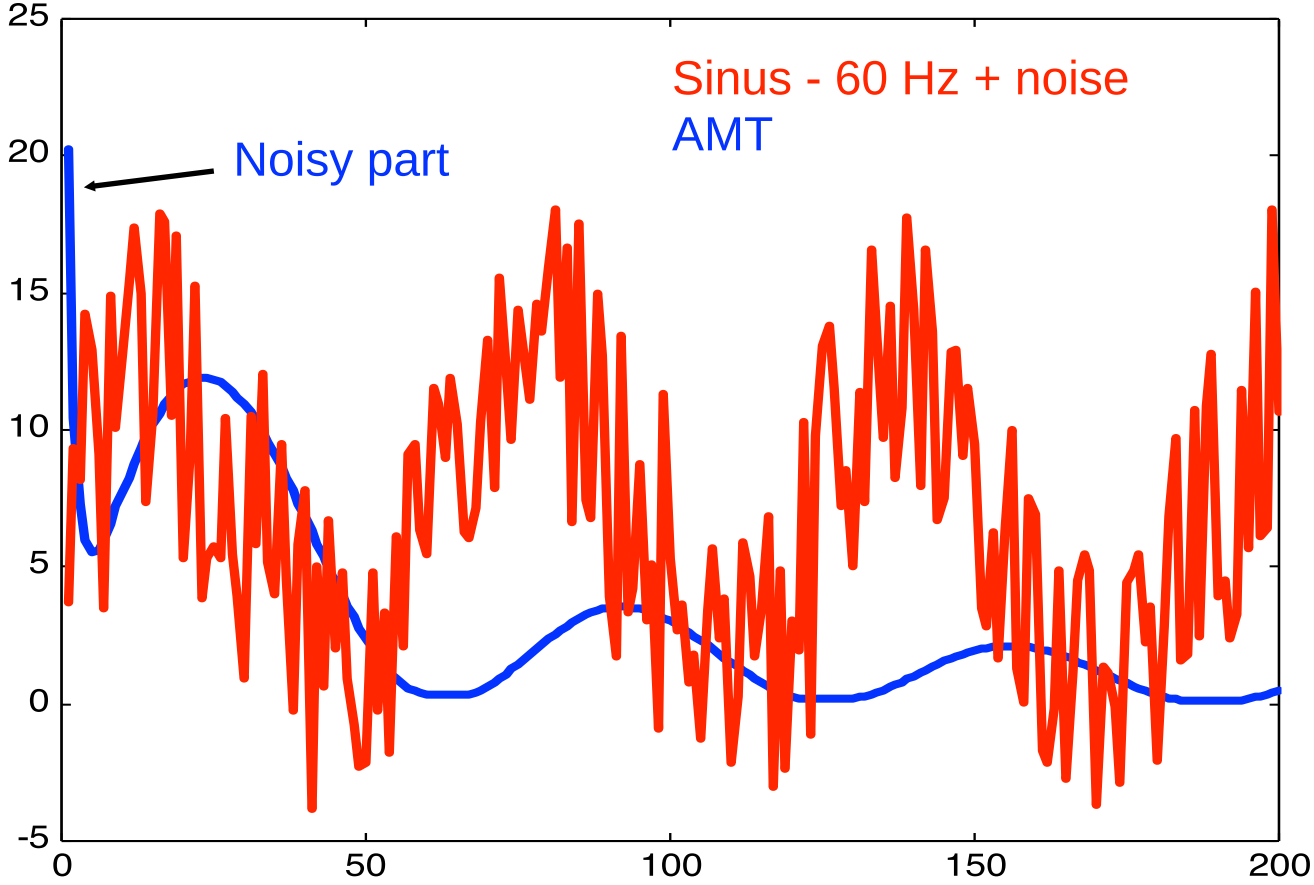
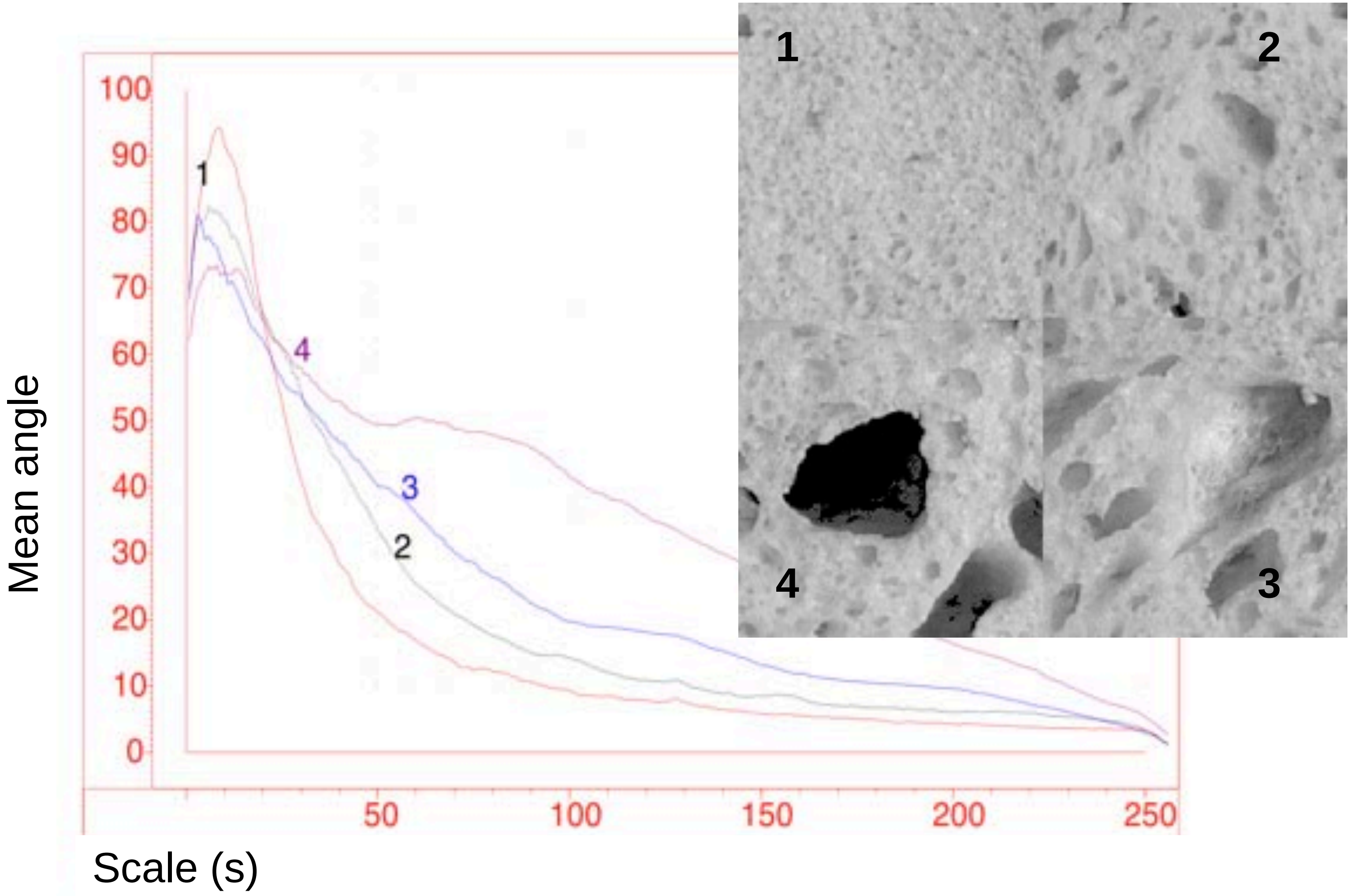
AMT spectrum of the sinus function



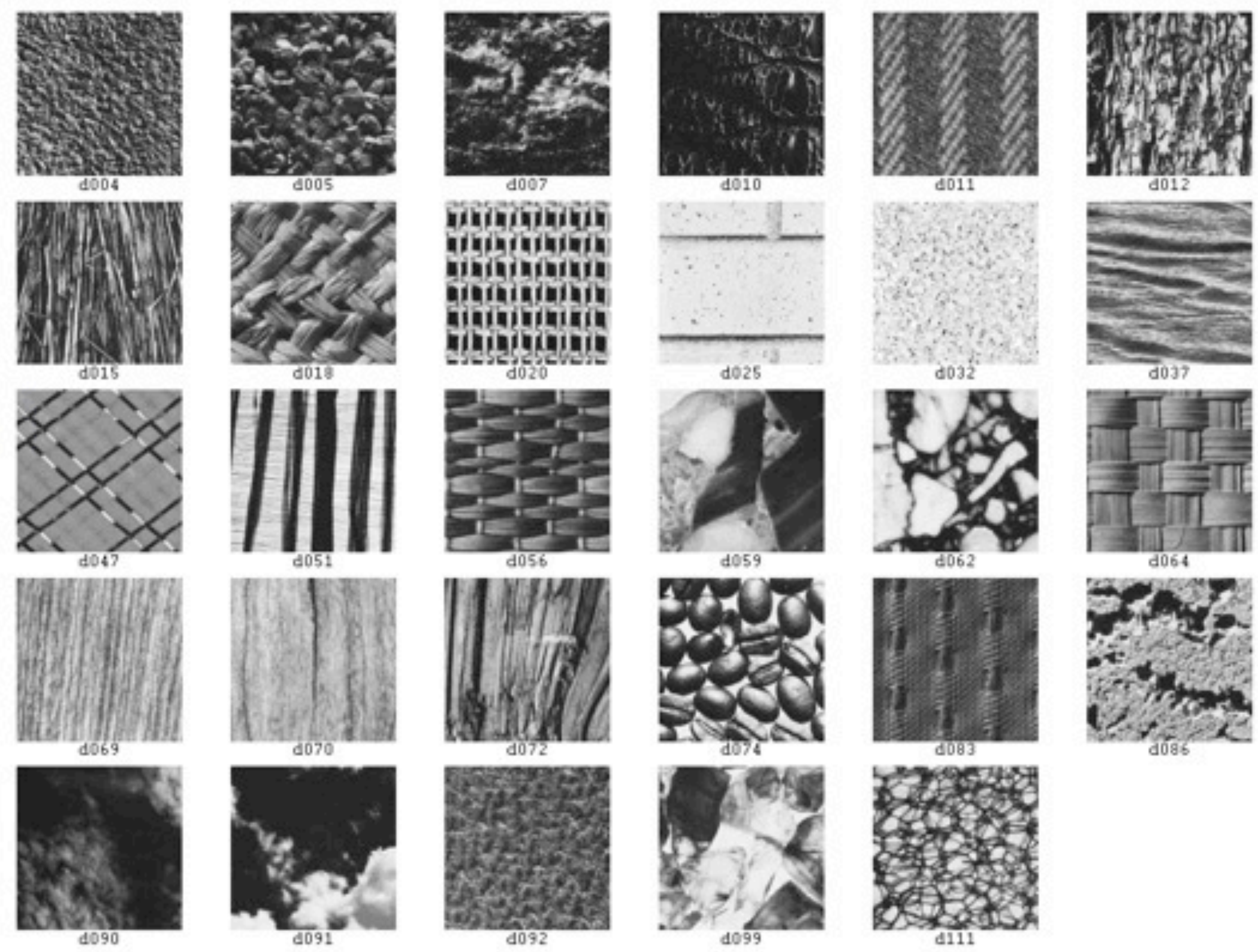
AMT spectrum from a noisy sinus function



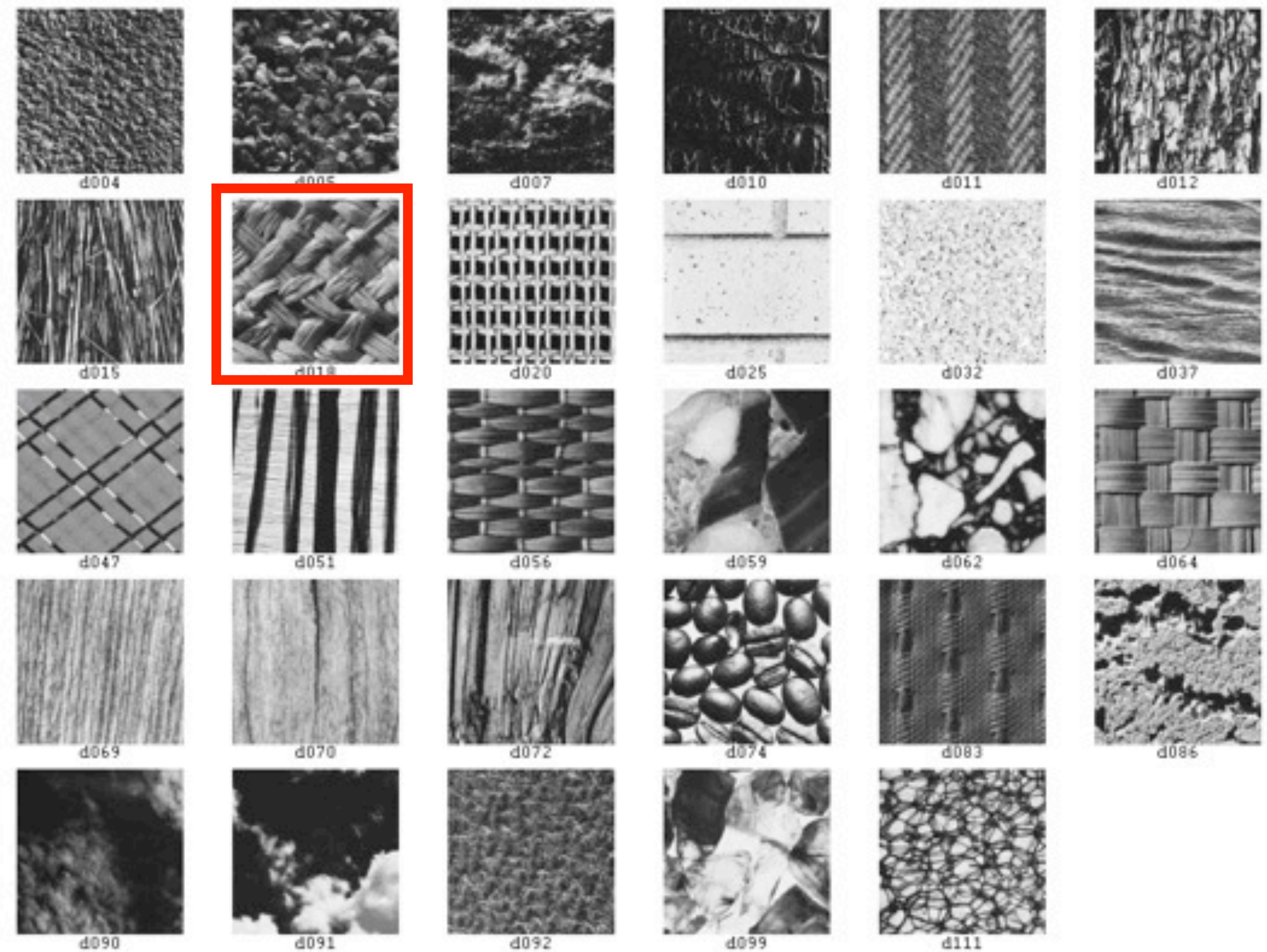
AMT spektra for different textures

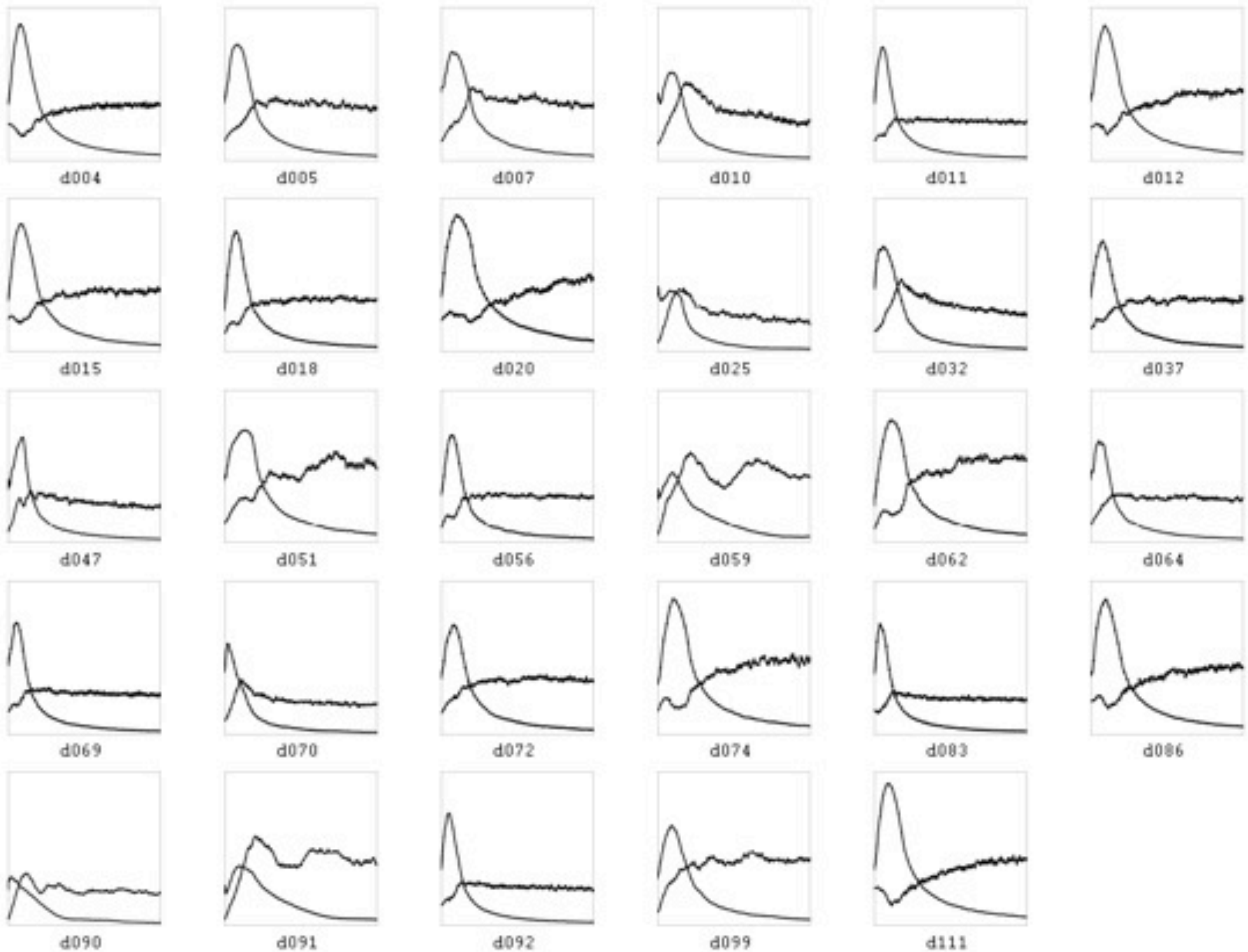


AMT applied on the BRODATZ texture database



AMT applied on the BRODATZ texture database

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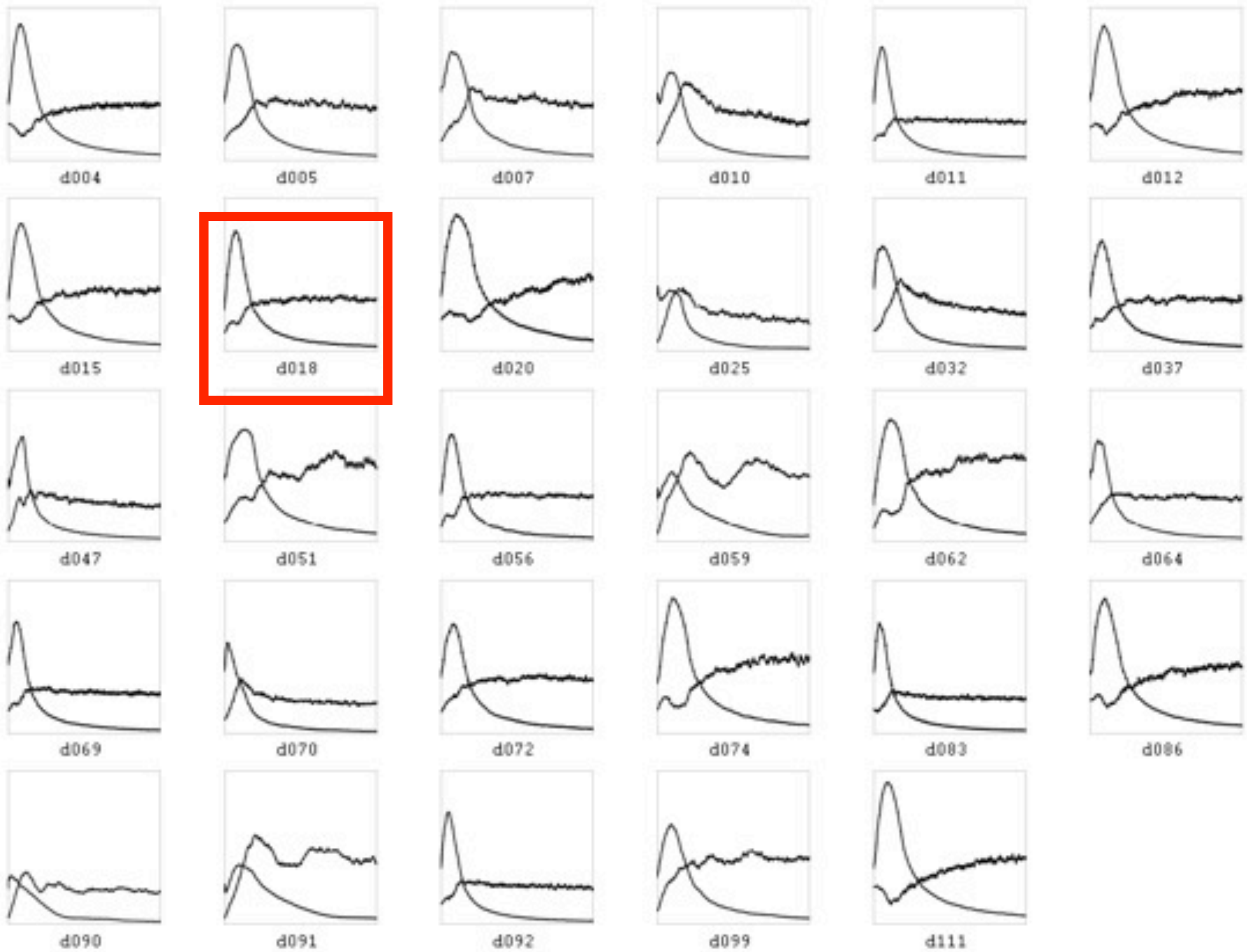
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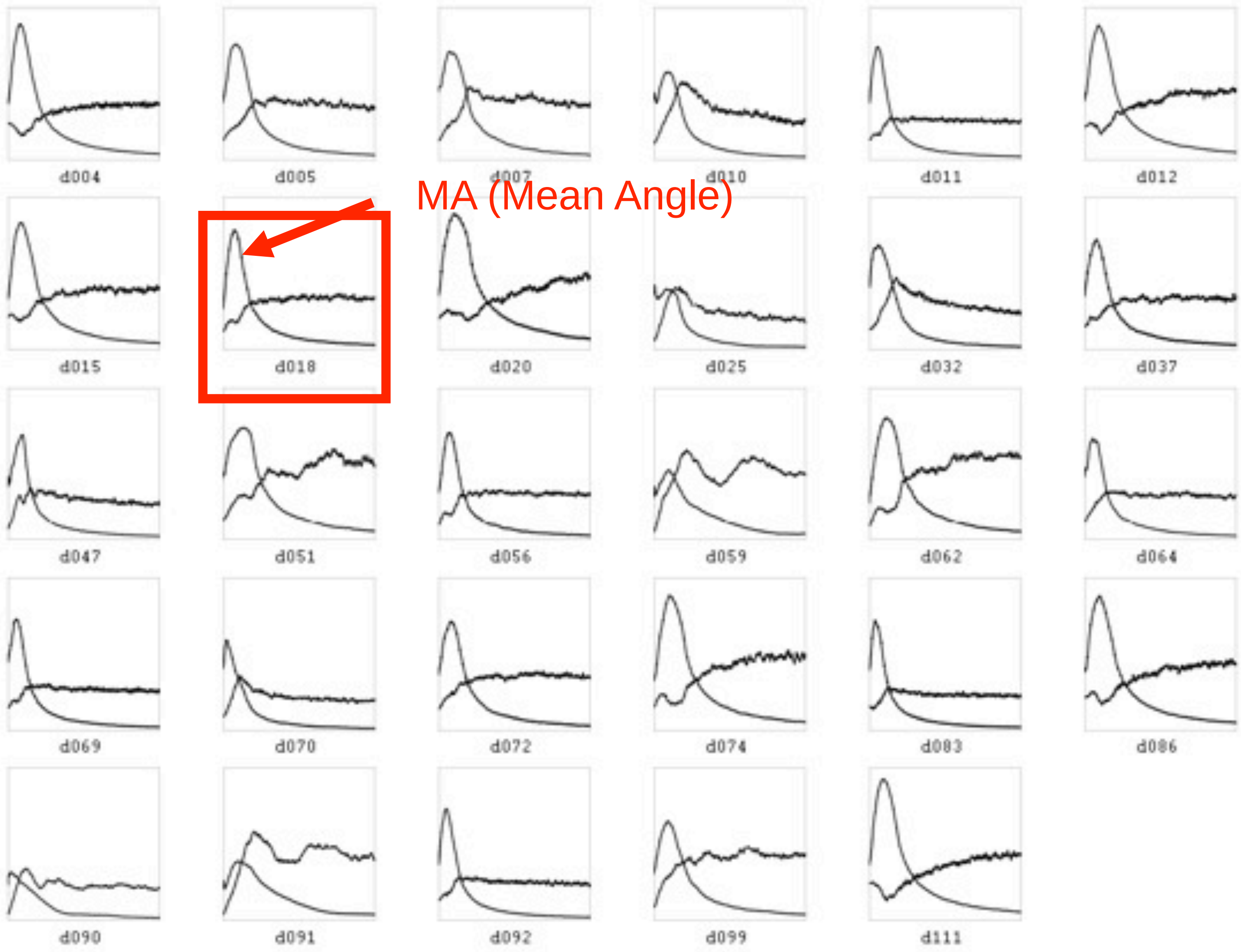
MA (Mean Angle)
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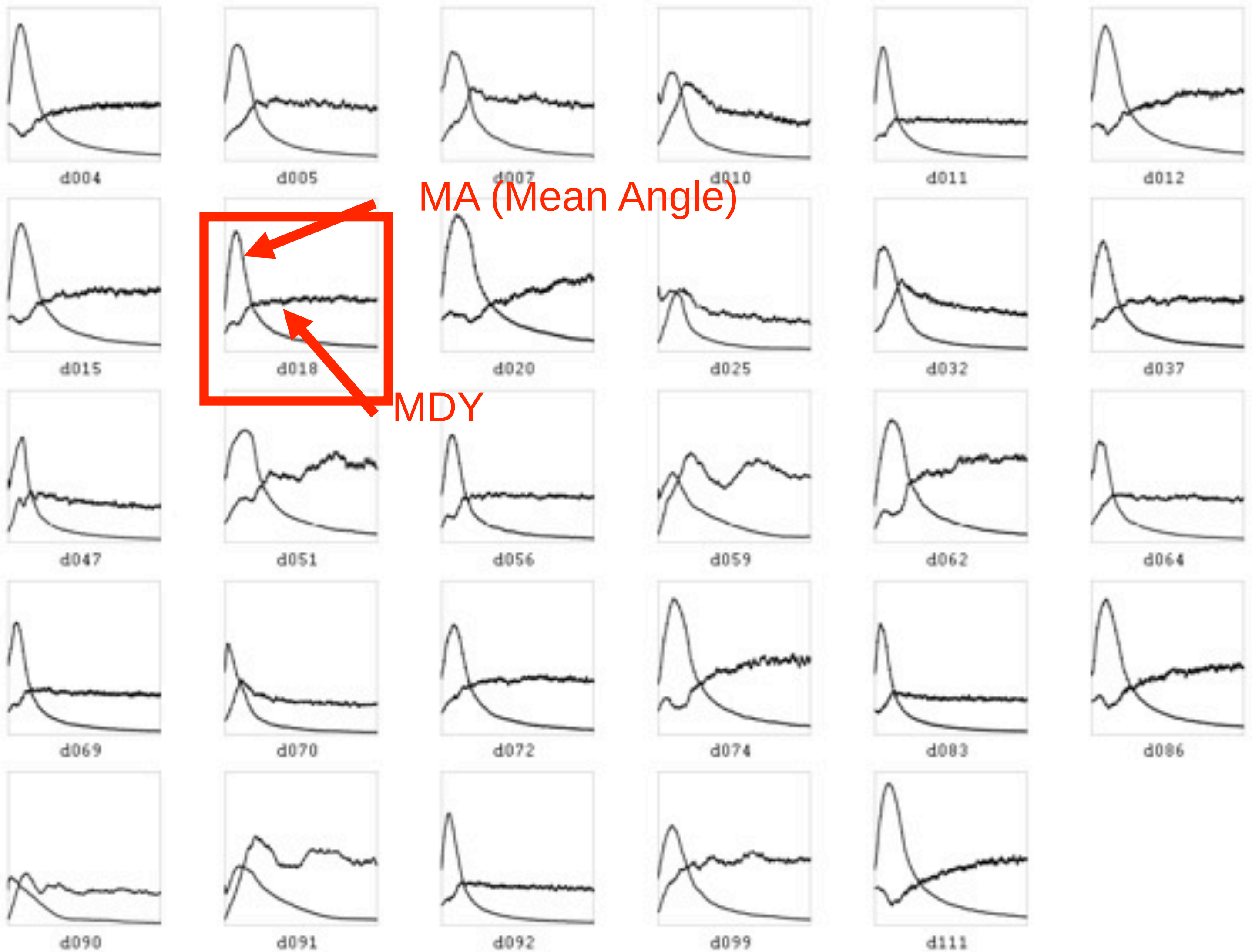
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Principal component analysis

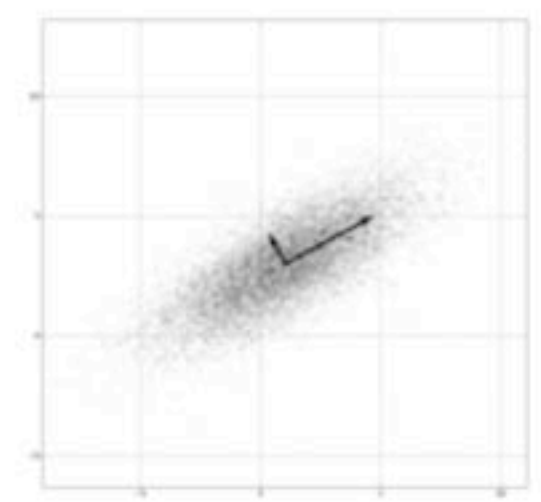
From Wikipedia, the free encyclopedia

"KLT" redirects here. For the Kanade–Lucas–Tomasi feature tracker used in computer vision, see Kanade–Lucas–Tomasi Feature Tracker.

This article or section appears to **contradict** itself. Please see its talk page for more information. *(May 2009)*

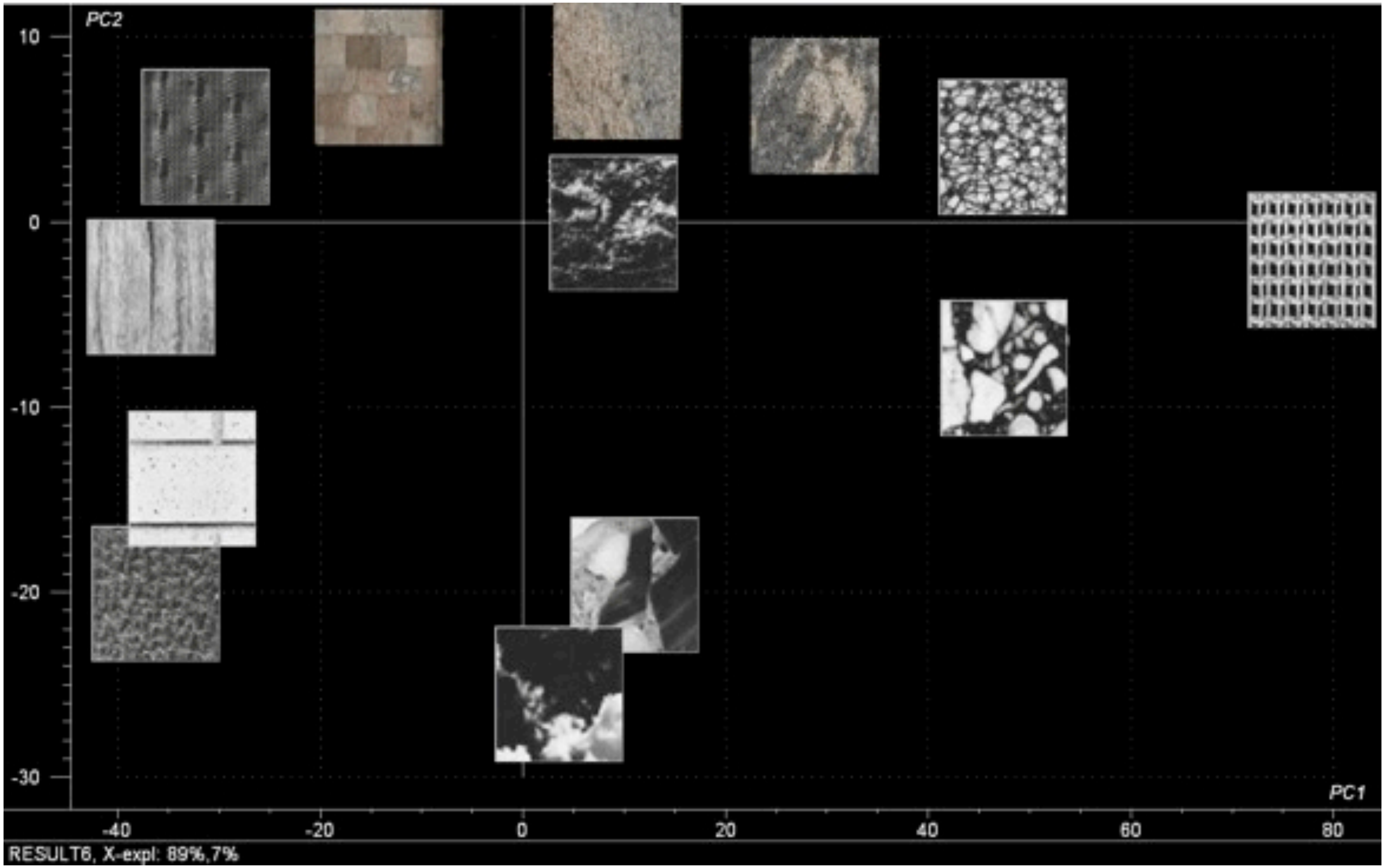
Principal component analysis (PCA) involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. Depending on the field of application, it is also named the discrete **Karhunen–Loève transform** (**K.L.T.**), the **Hotelling transform** or **proper orthogonal decomposition** (**POD**).

PCA was invented in 1901 by Karl Pearson.[1] Now it is mostly used as a tool in exploratory data analysis and for making predictive models. PCA involves the calculation of the eigenvalue decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centering the data for each attribute. The results of a PCA are usually discussed in terms of component scores and loadings (Shaw, 2003).

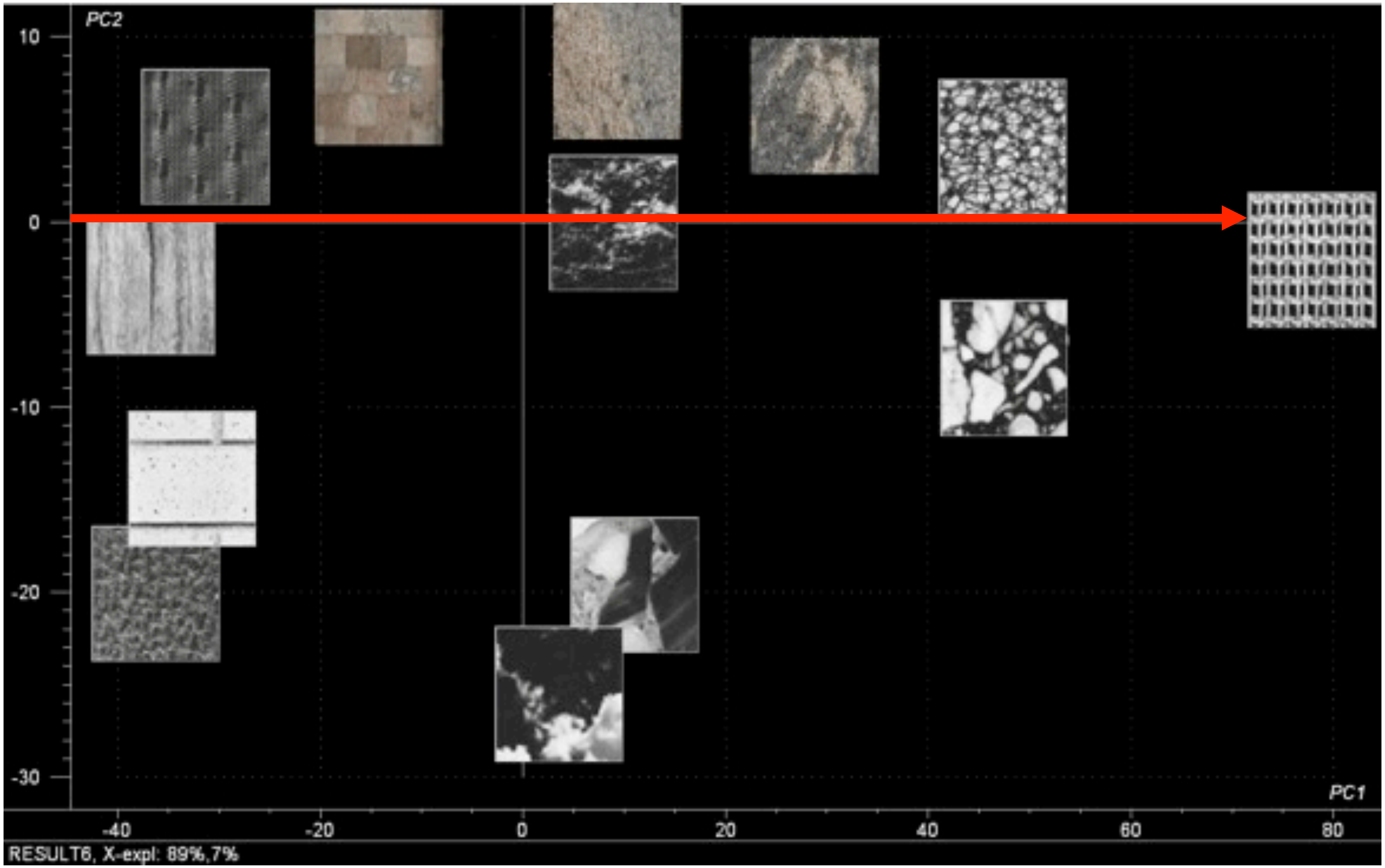


PCA of a multivariate Gaussian distribution centered at (1,3) with a standard deviation of 3 in roughly the (0.878, 0.478) direction and of 1 in the orthogonal

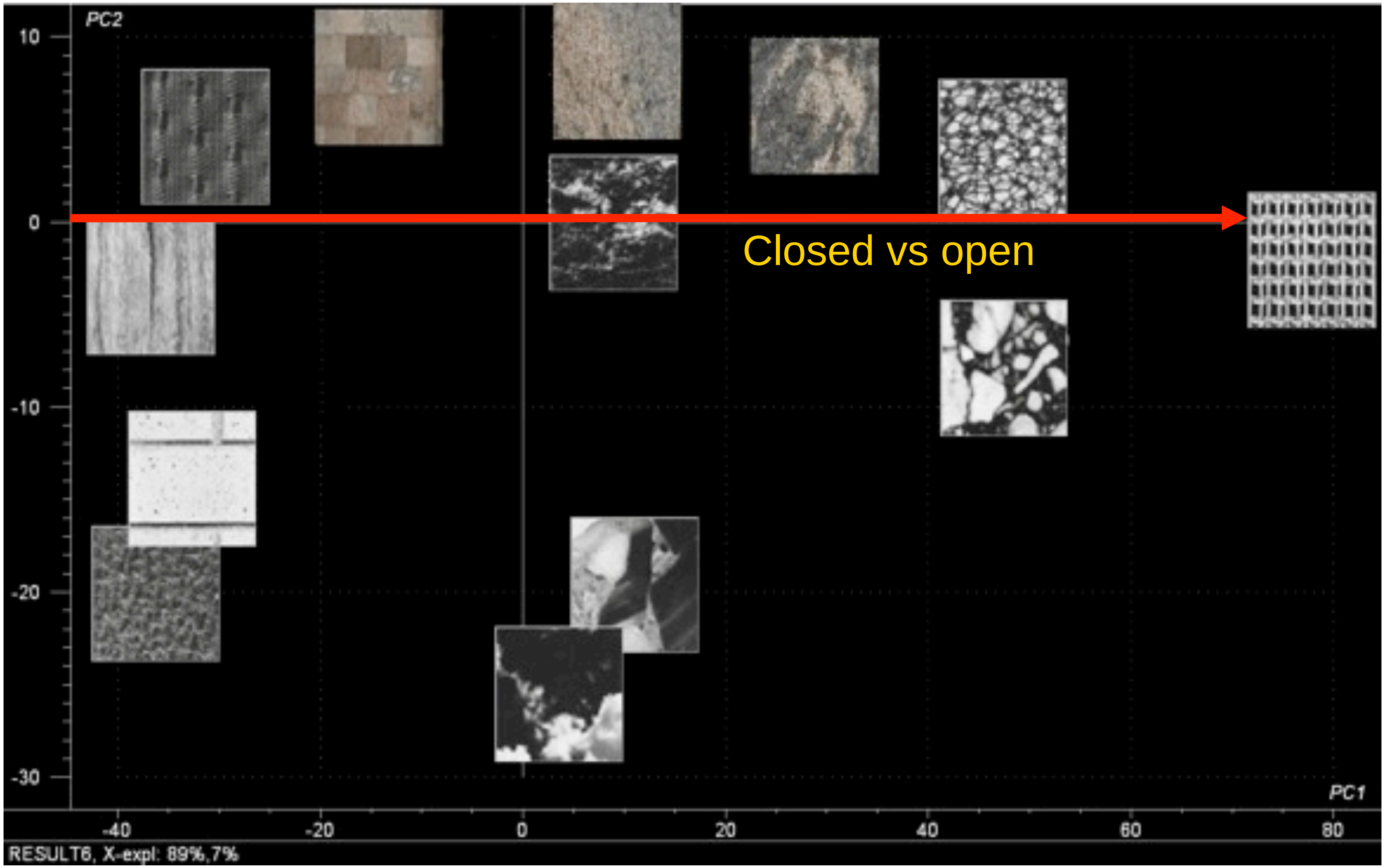
Texture image PCA



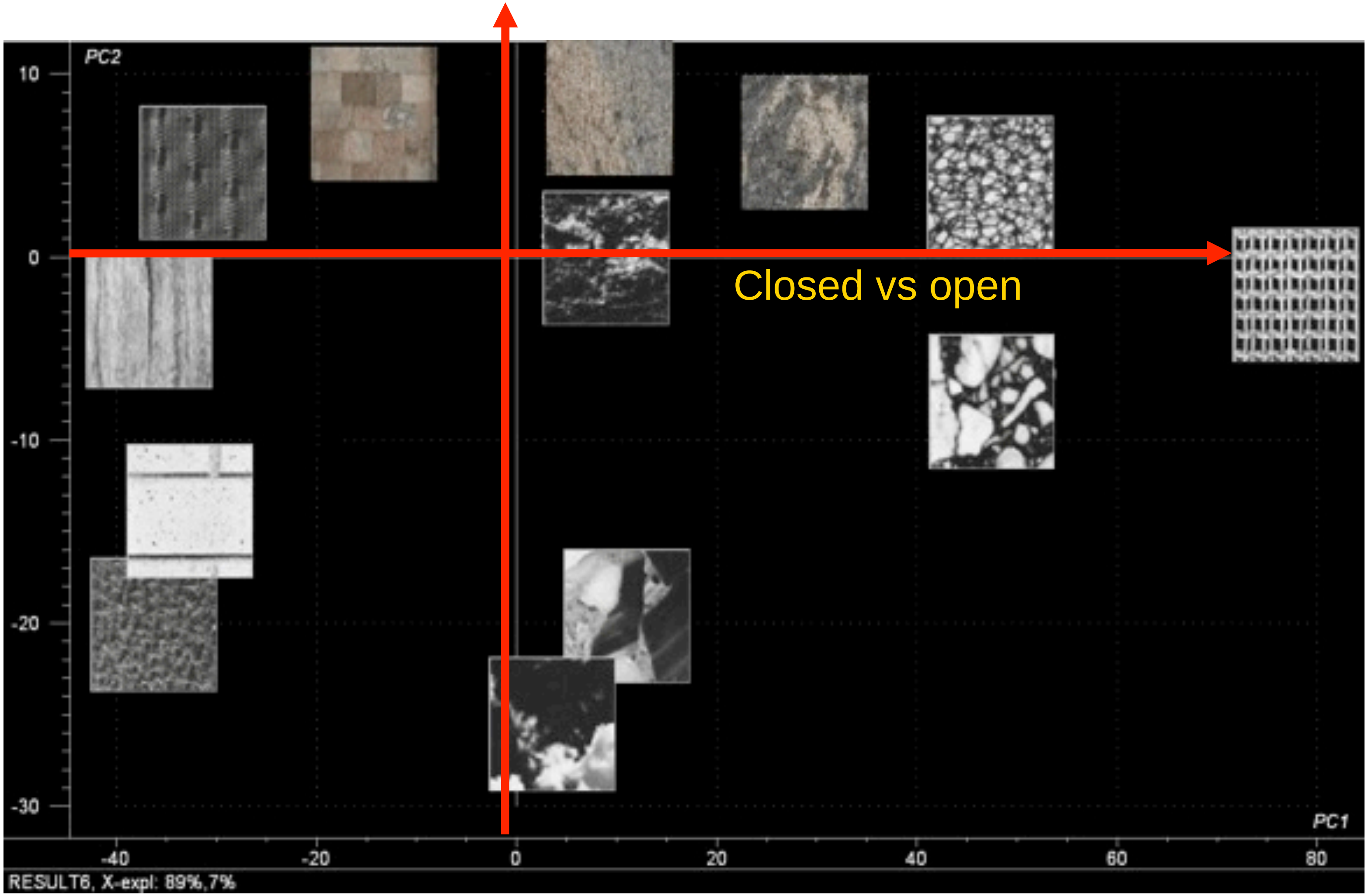
Texture image PCA



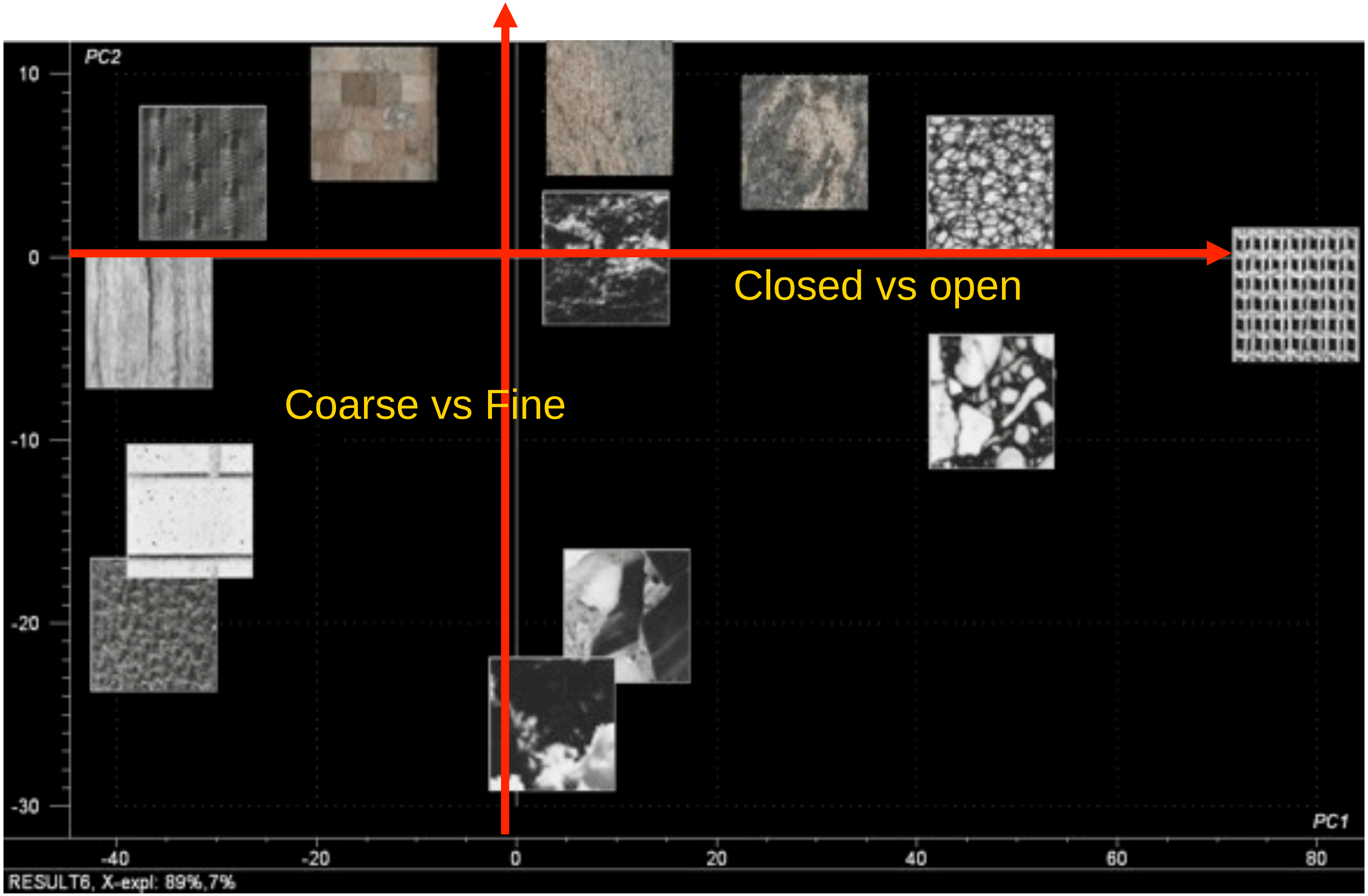
Texture image PCA



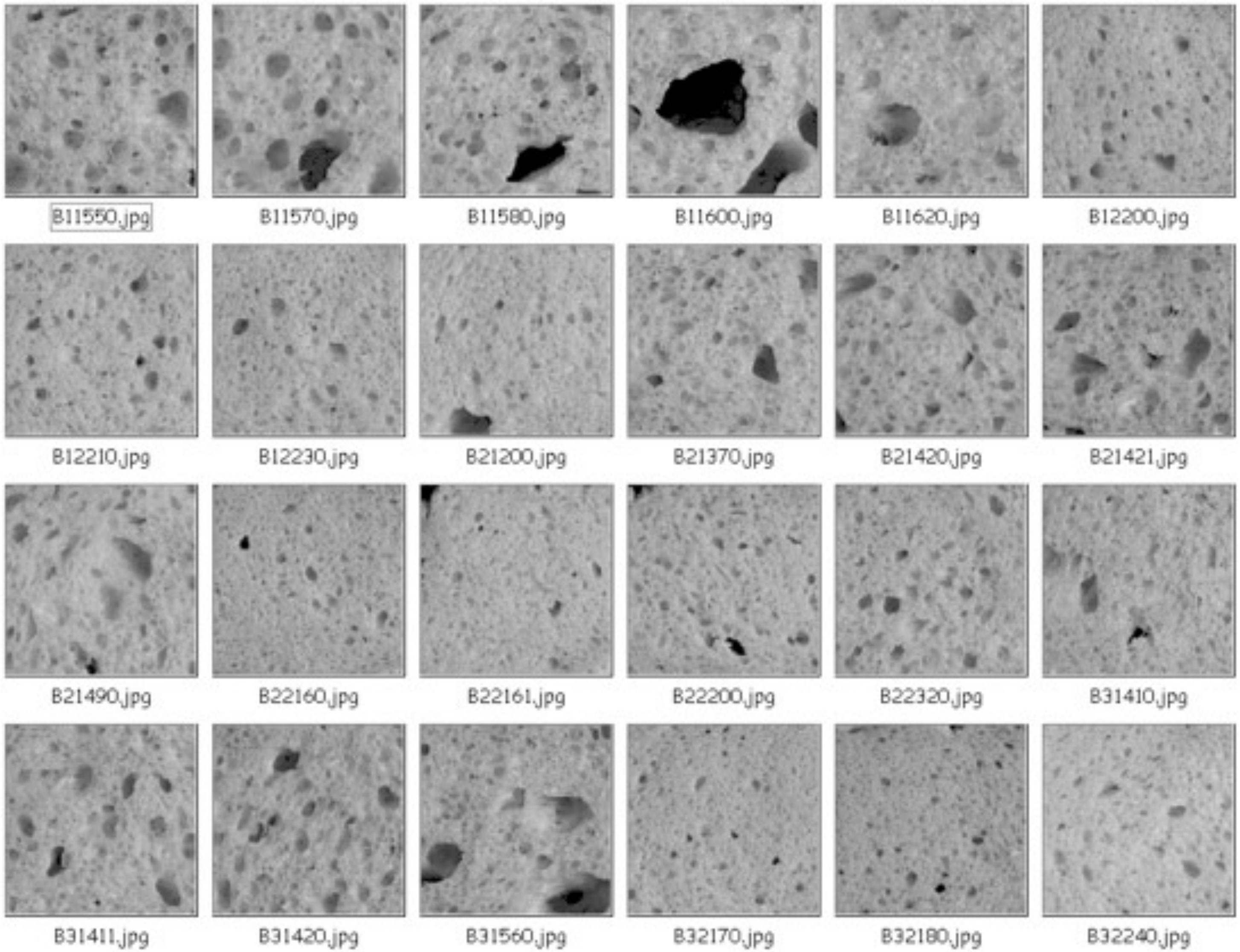
Texture image PCA



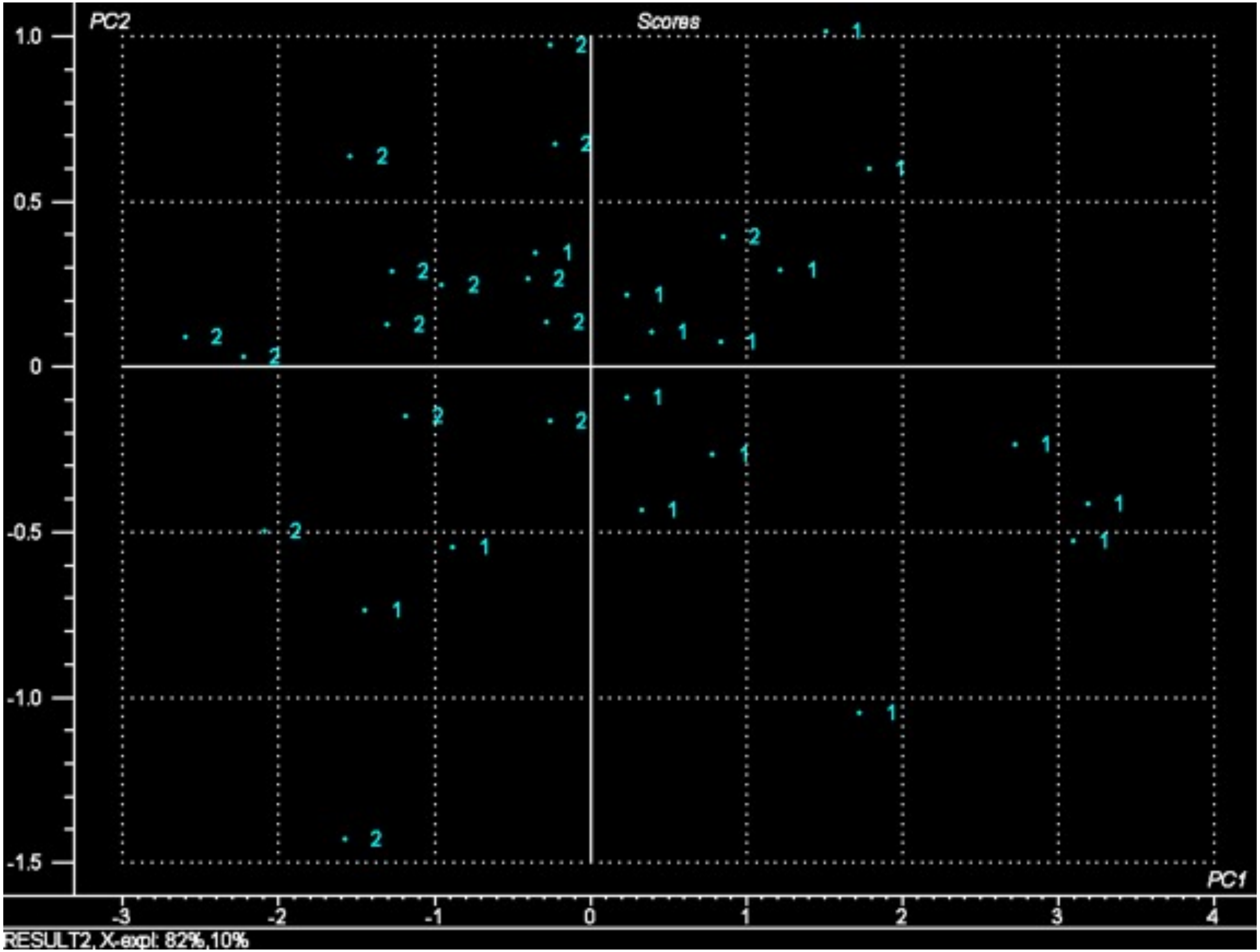
Texture image PCA



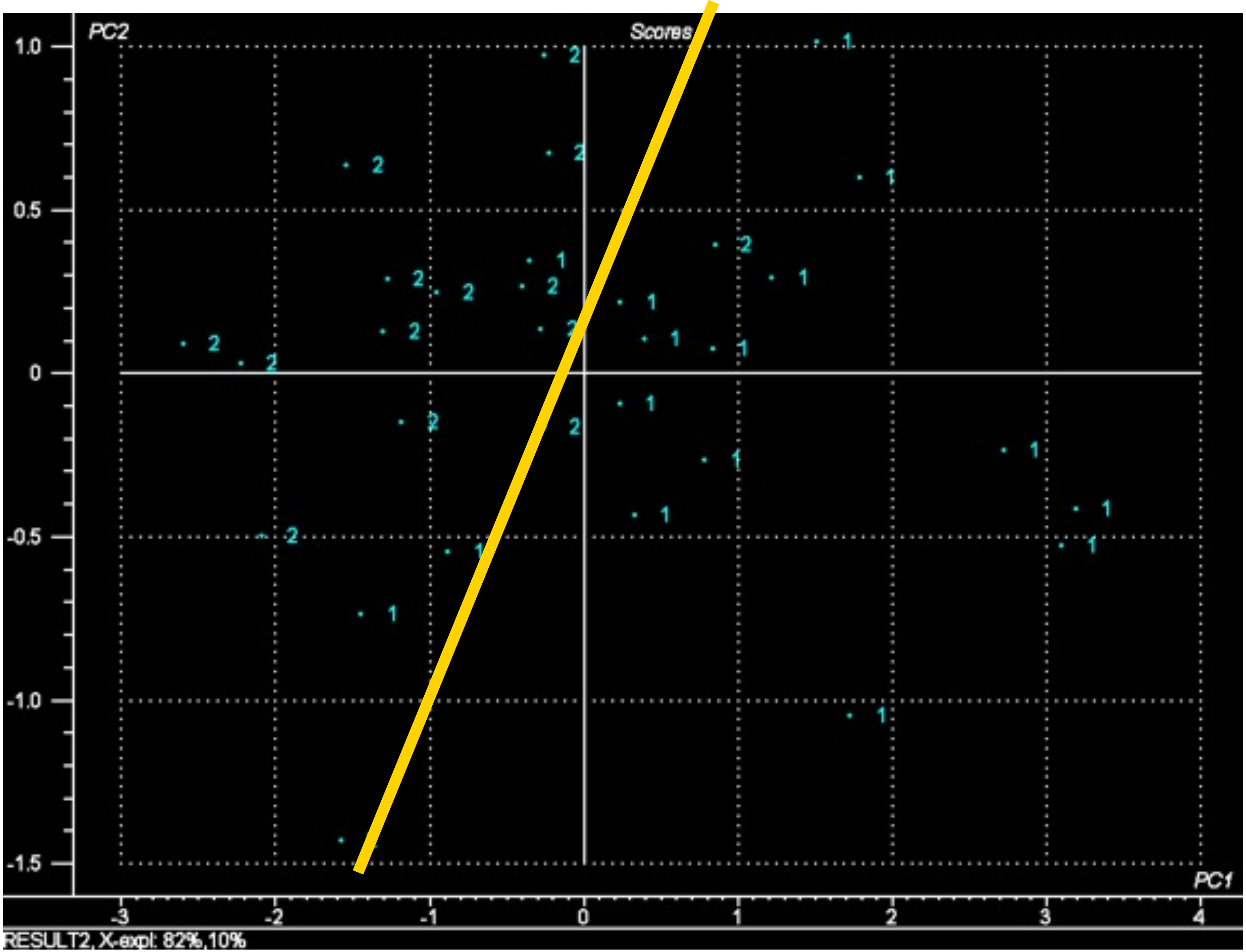
Baguette database



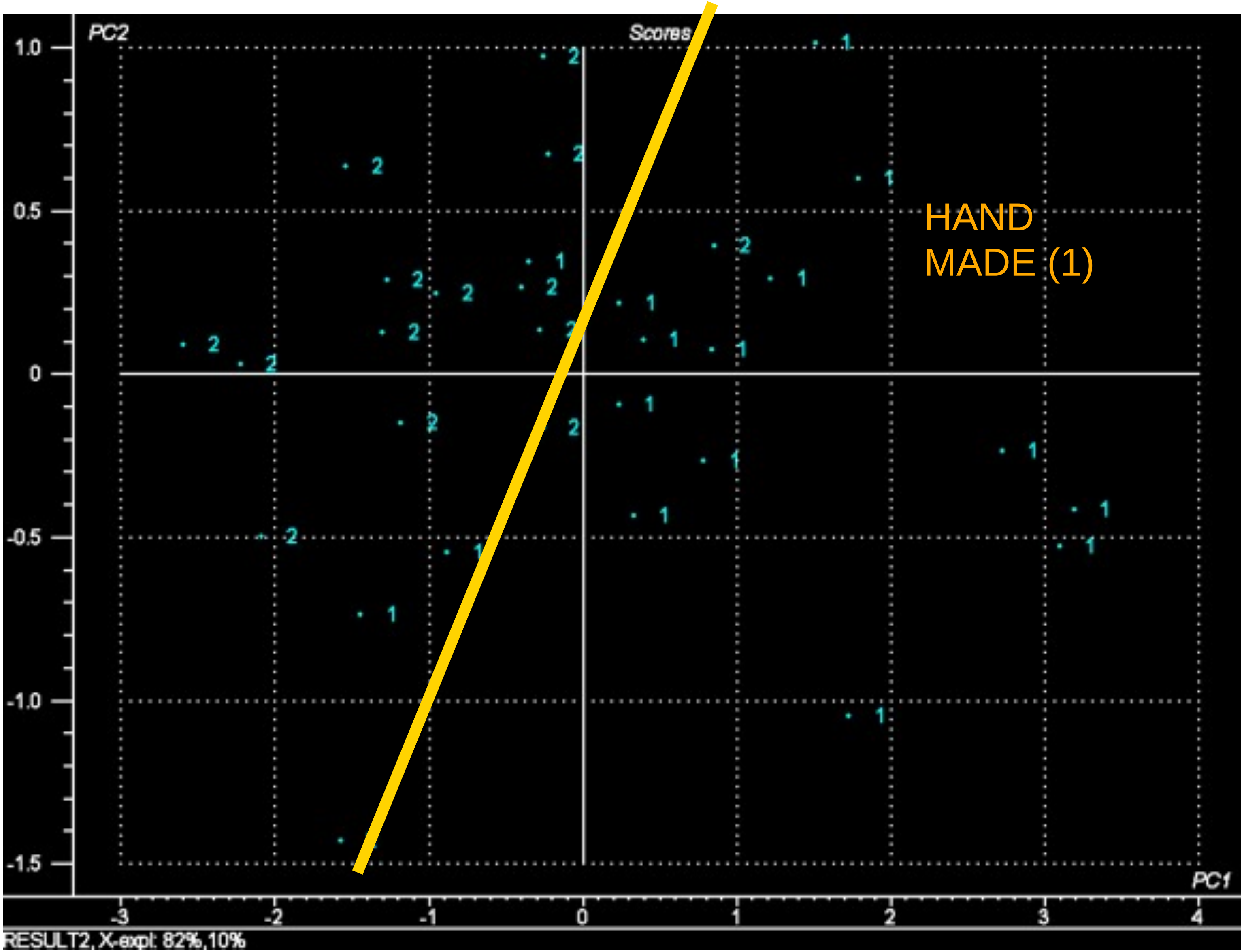
PCA based on AMT spectra



PCA based on AMT spectra



PCA based on AMT spectra



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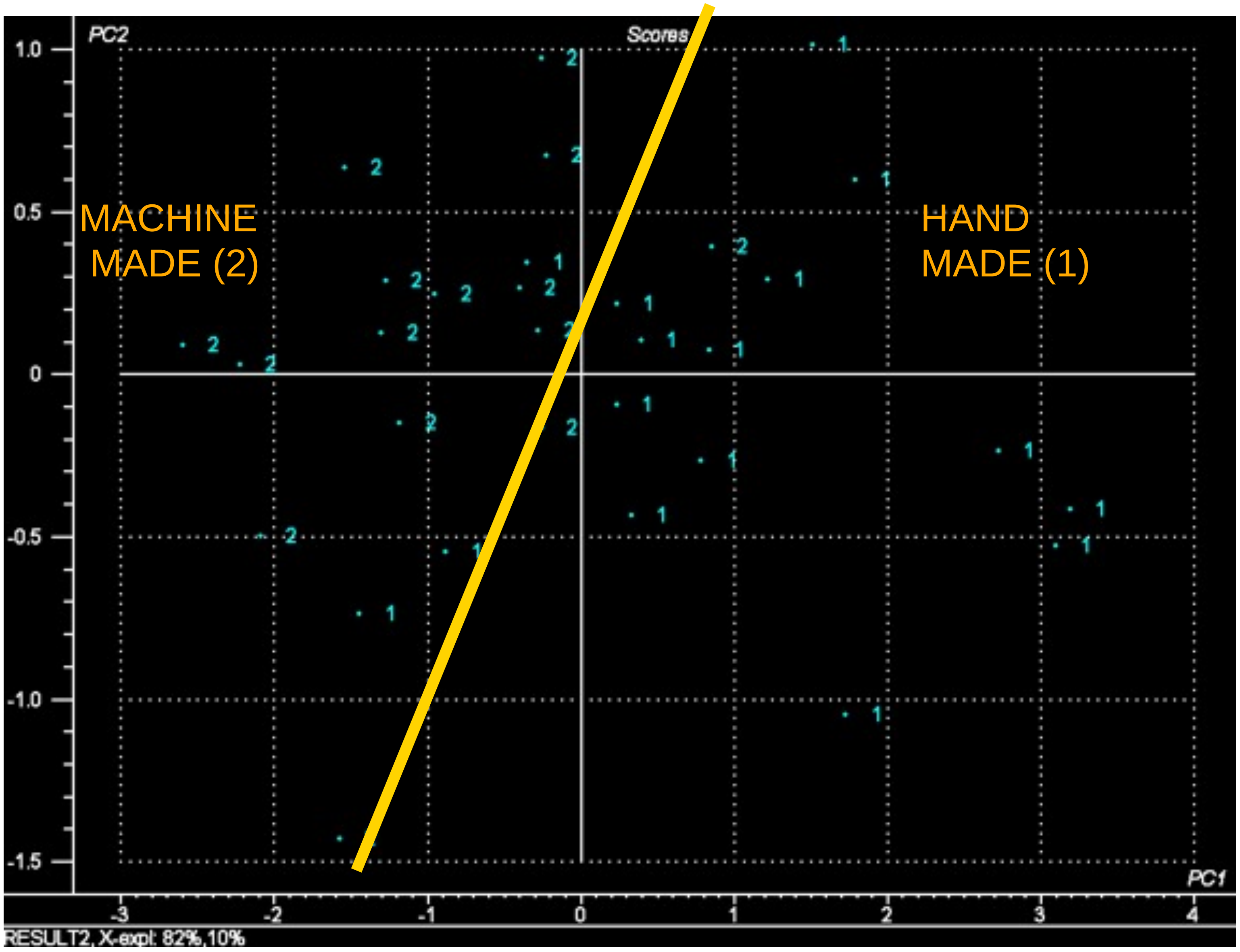

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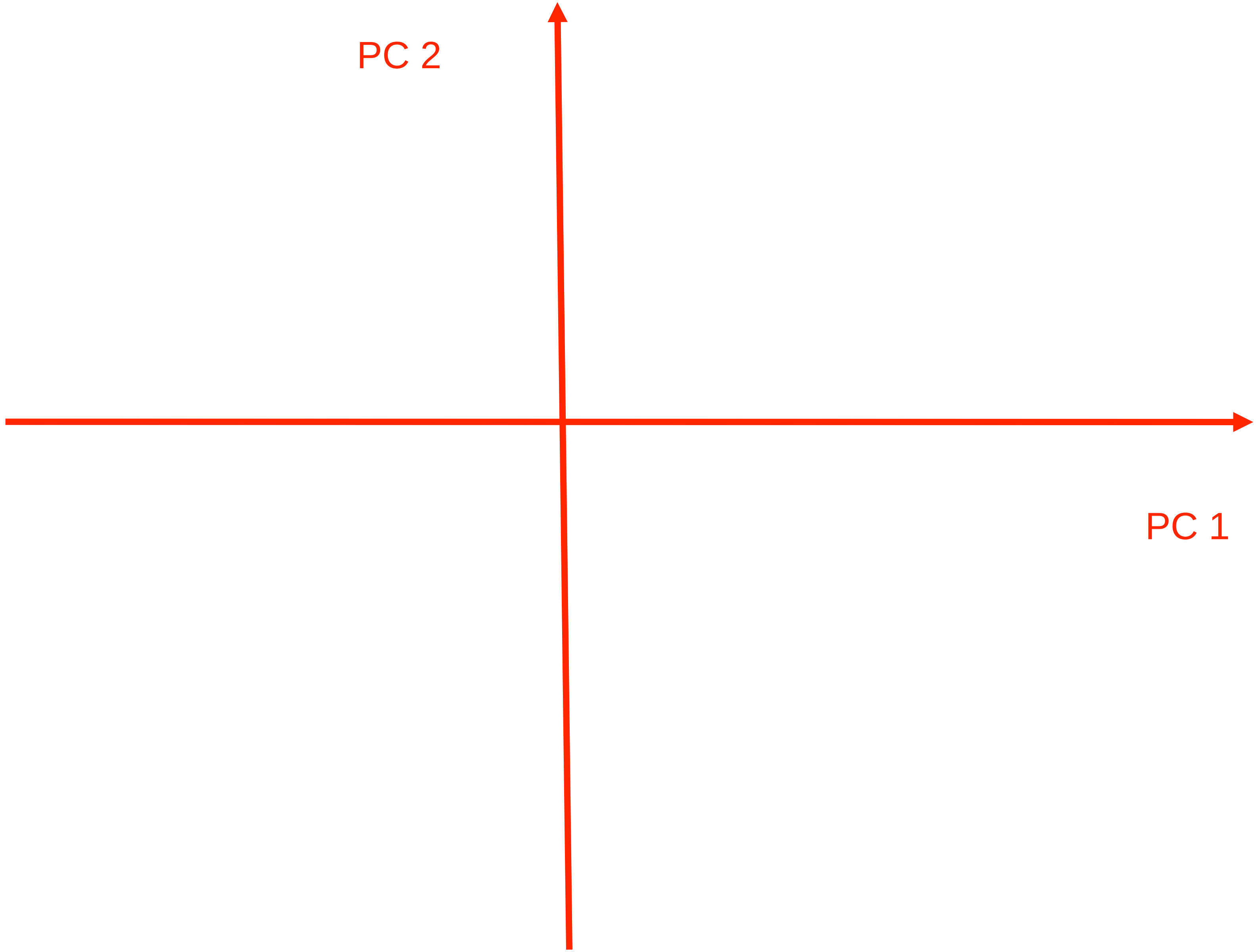
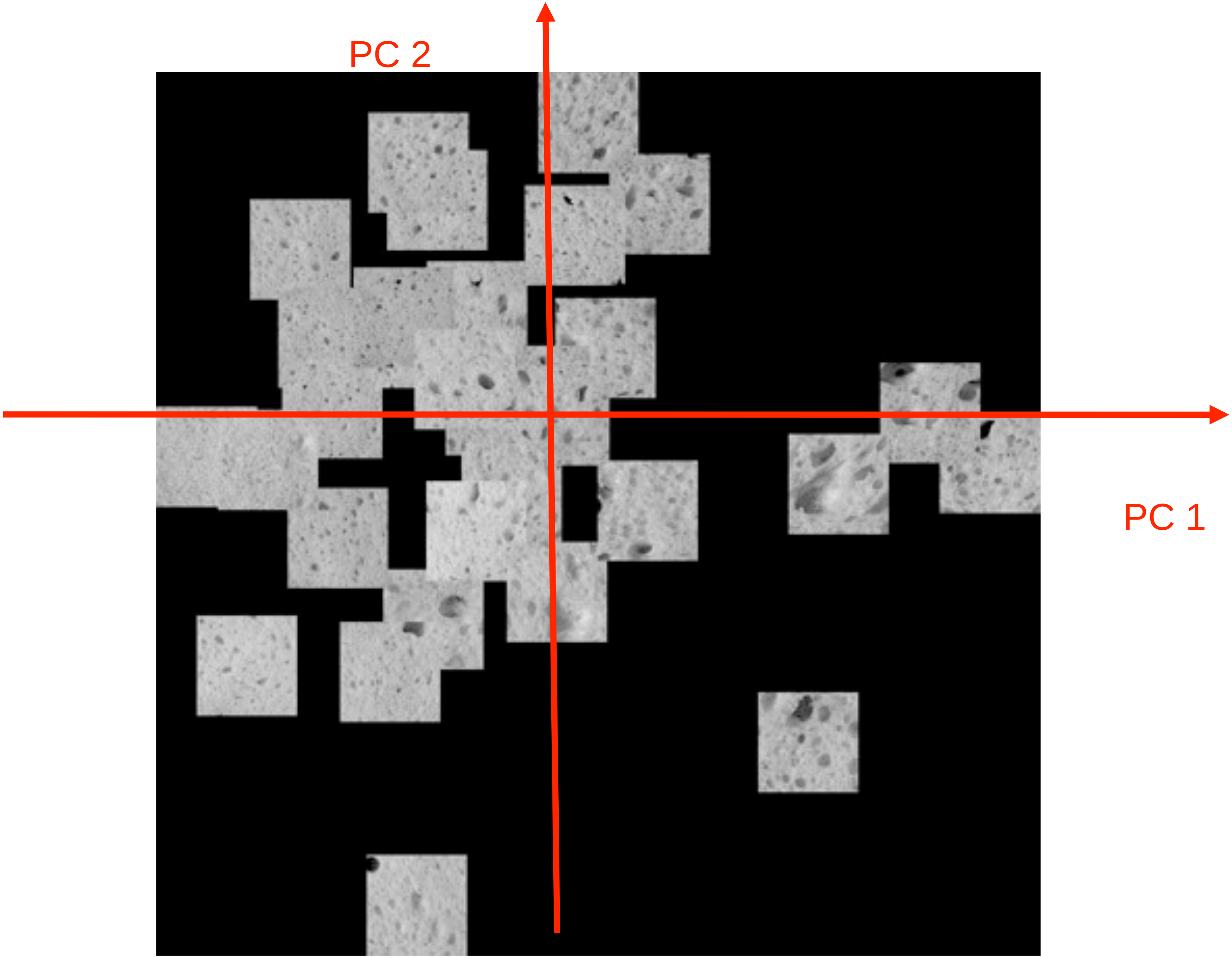
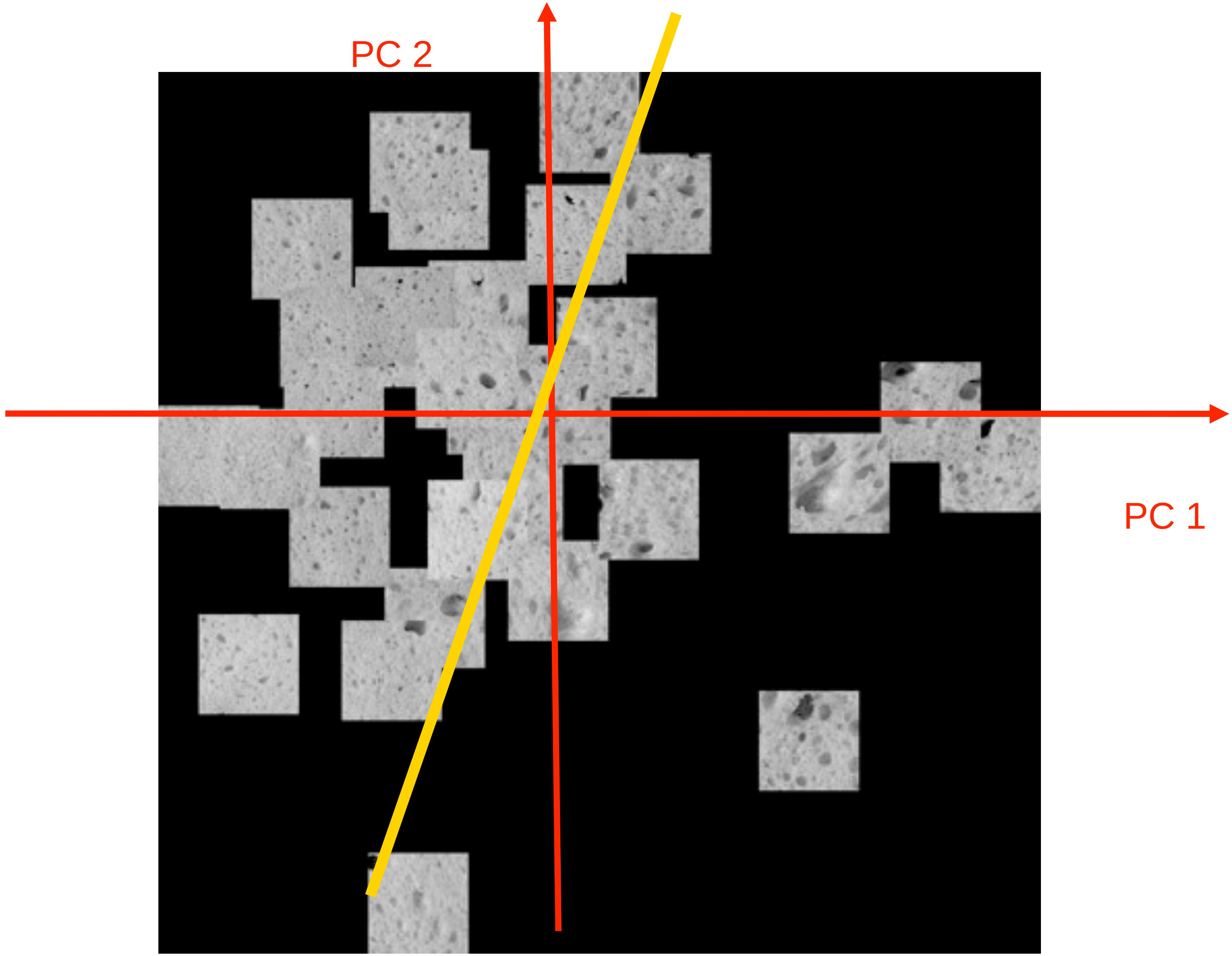
PCA based on AMT spectra



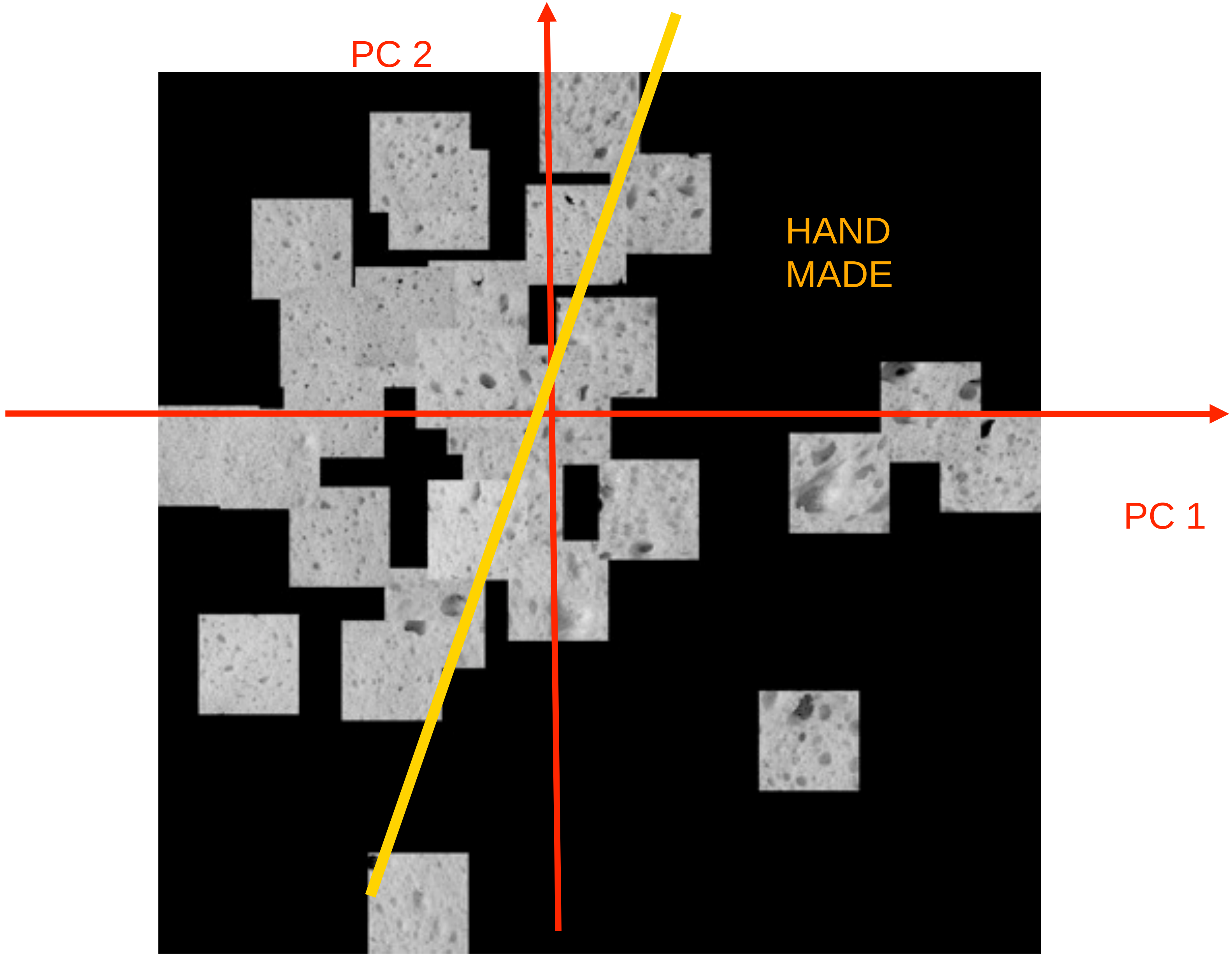
PCA based on AMT spectra



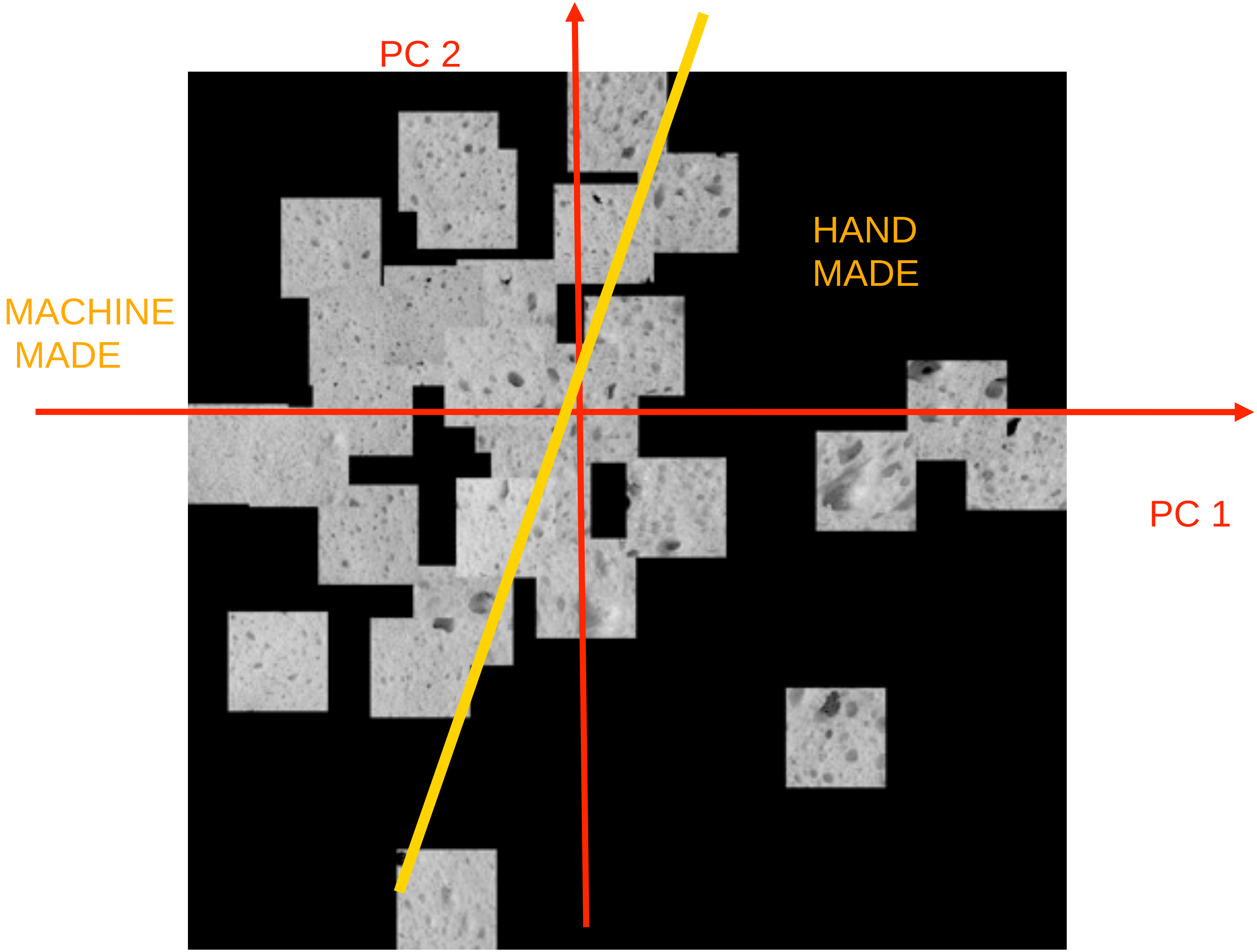
PCA based on AMT spectra



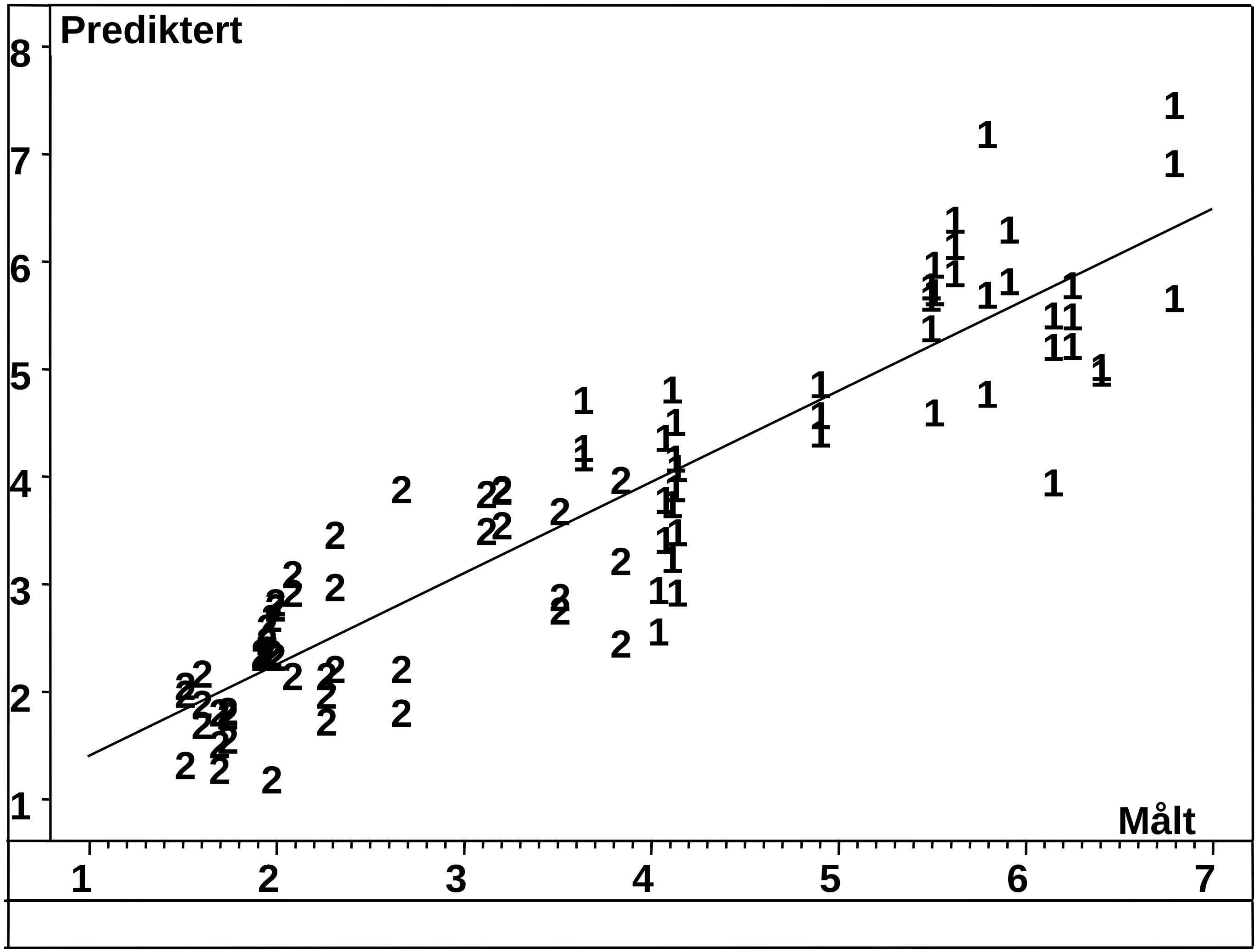
PCA based on AMT spectra



PCA based on AMT spectra



Prediksjon av sensorisk porøsitet (bakemetode)



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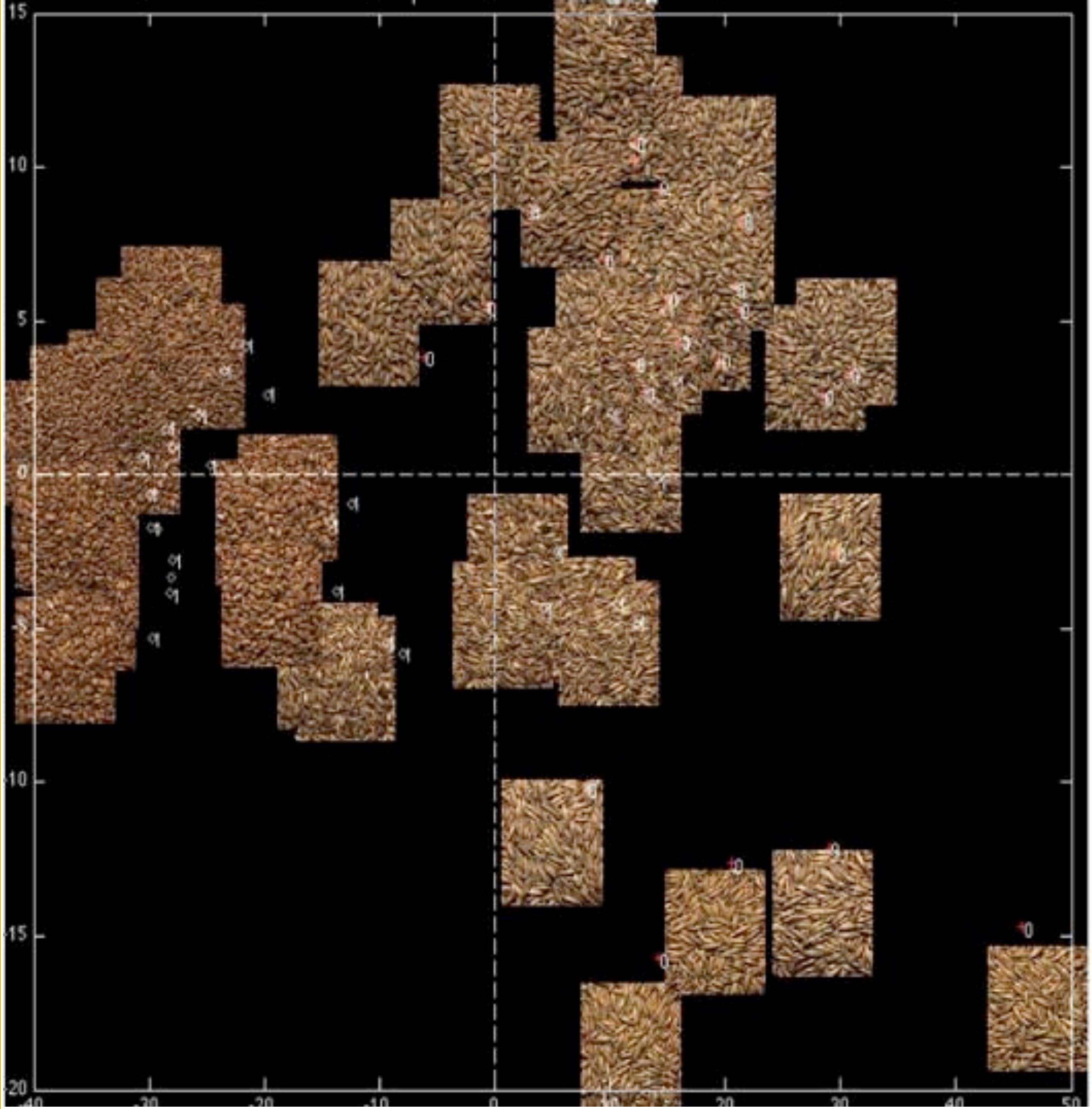
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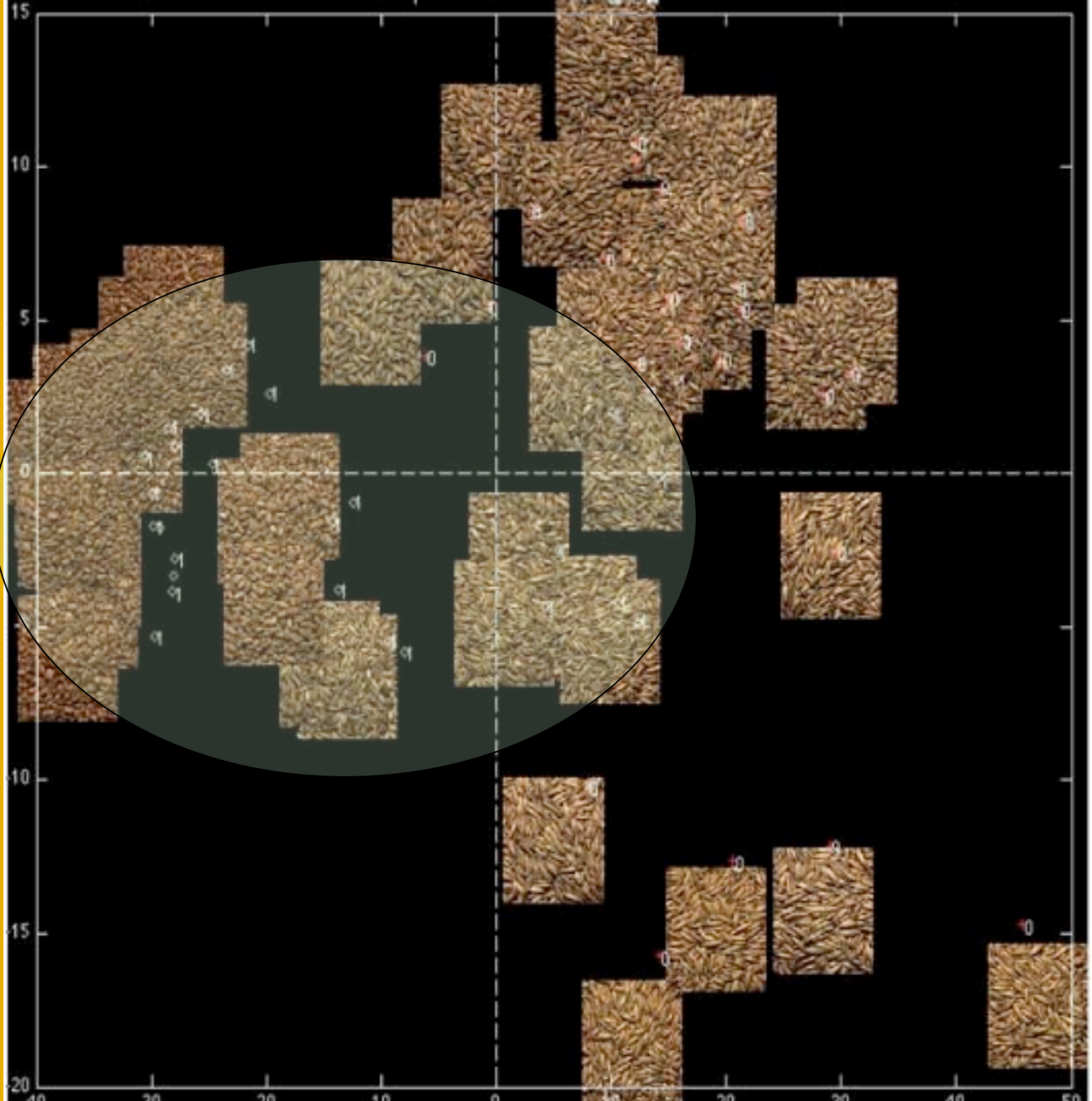


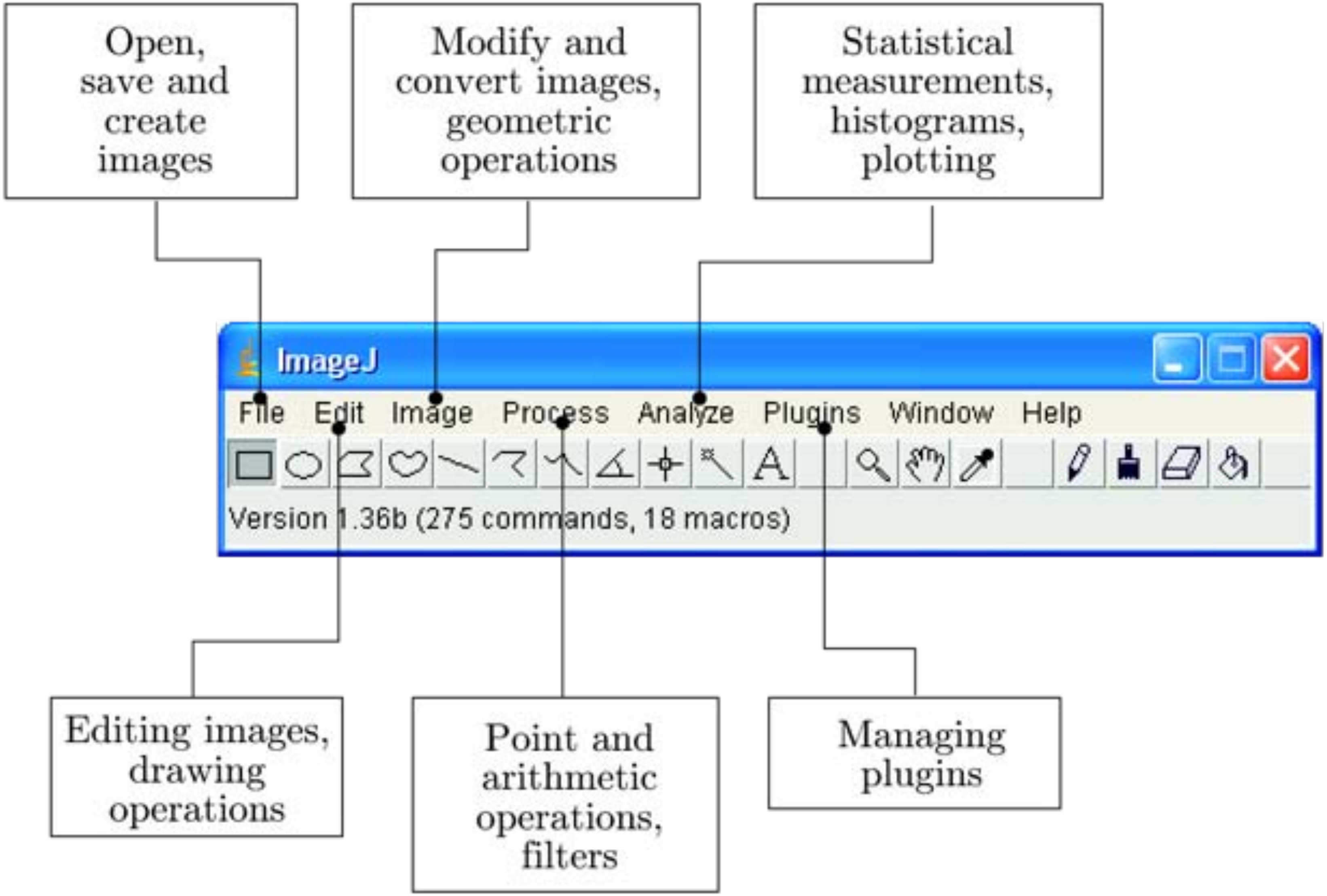
27

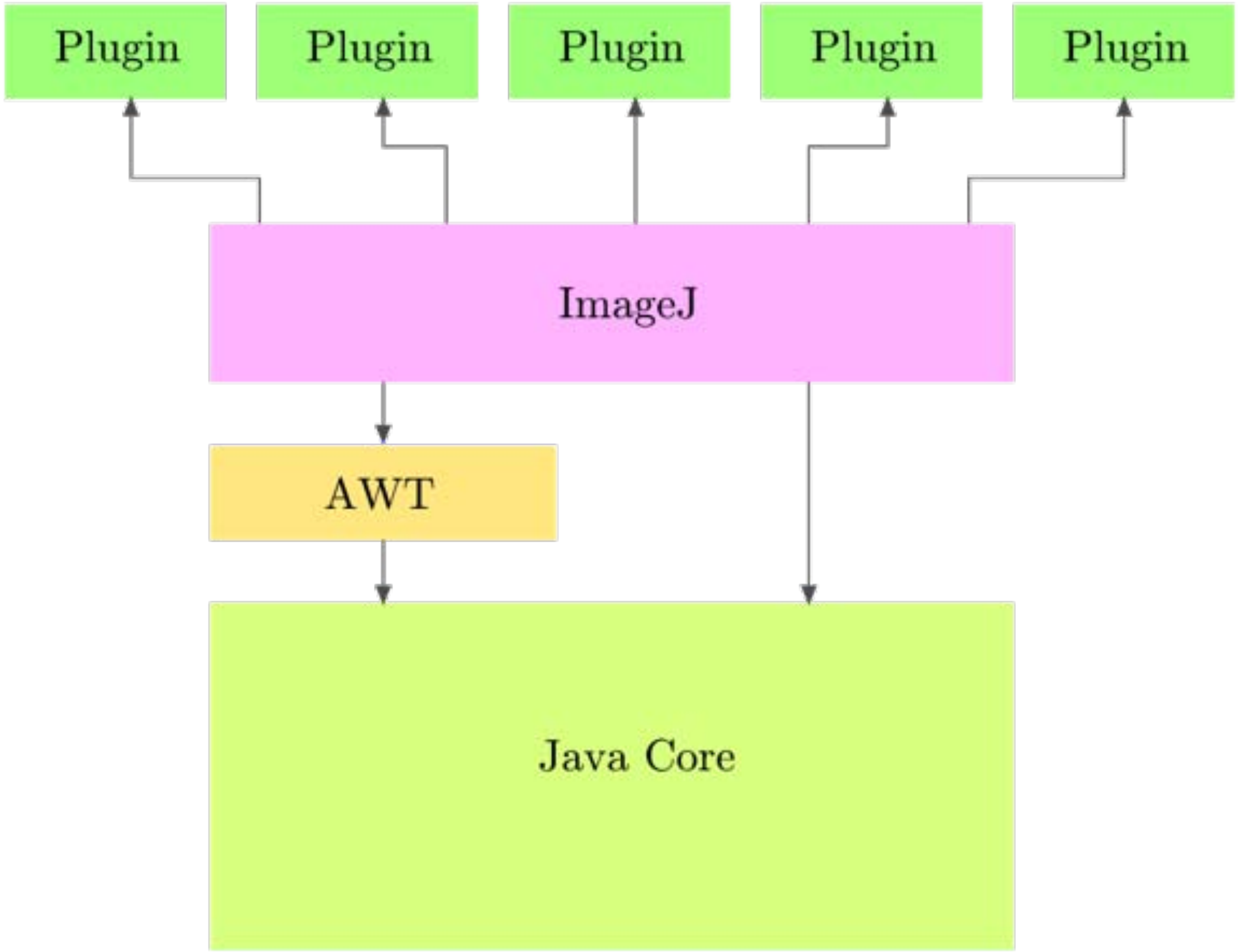
The Open Source project

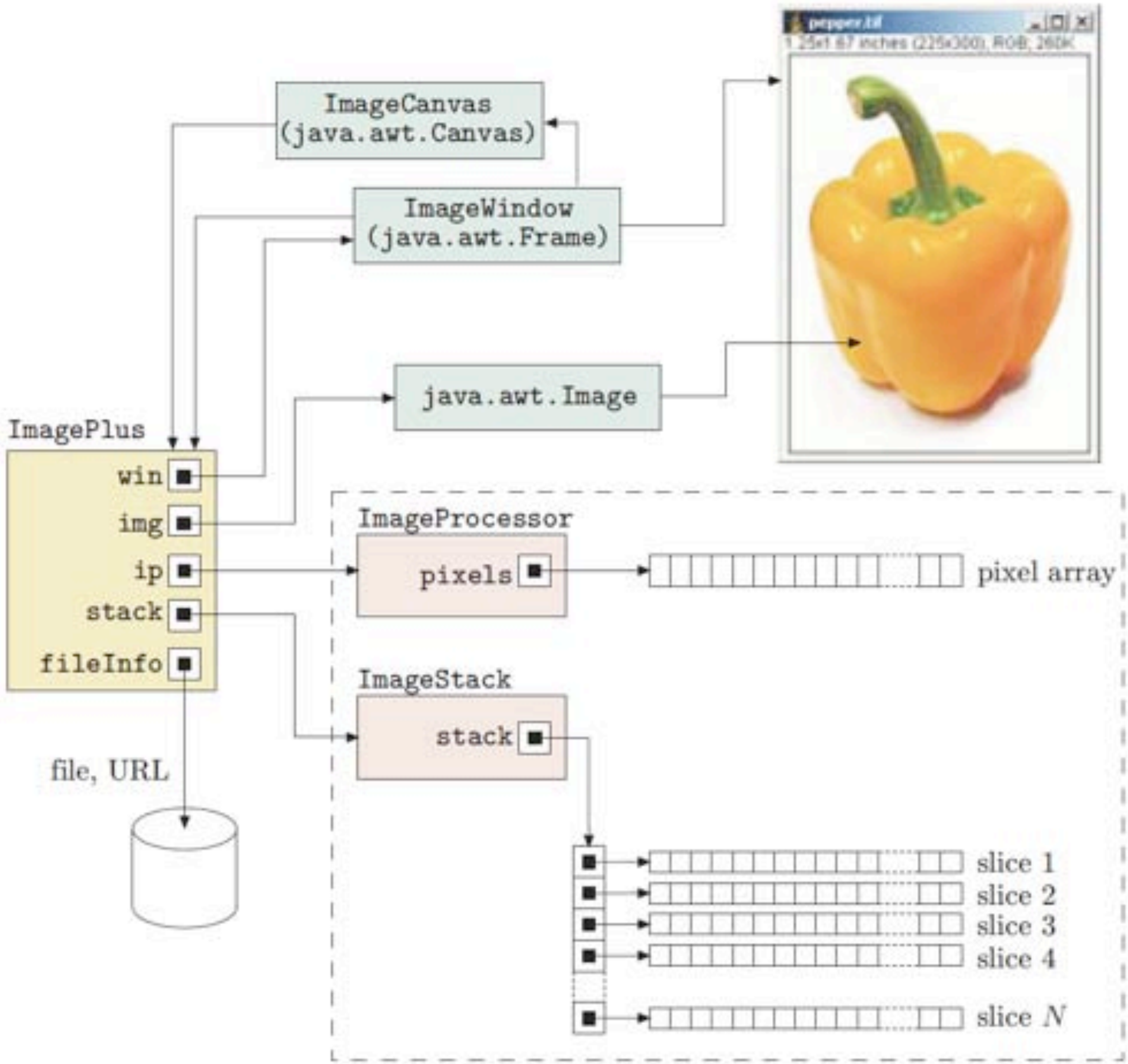
- ImageJ is selected as a good candidate for the software toolkit
- ImageJ plugins
  - AMT (Angle Measure Technique)
  - GLCM (Gray Level Coocurence Matrix)
  - SVD (Singular Value Decomposition)
  - MIA (Multivariate Image Analysis in progress)

Development environement

- ImageJ source
- Netbeans IDE
- Plugins are written by using IJ class frame and standard Java

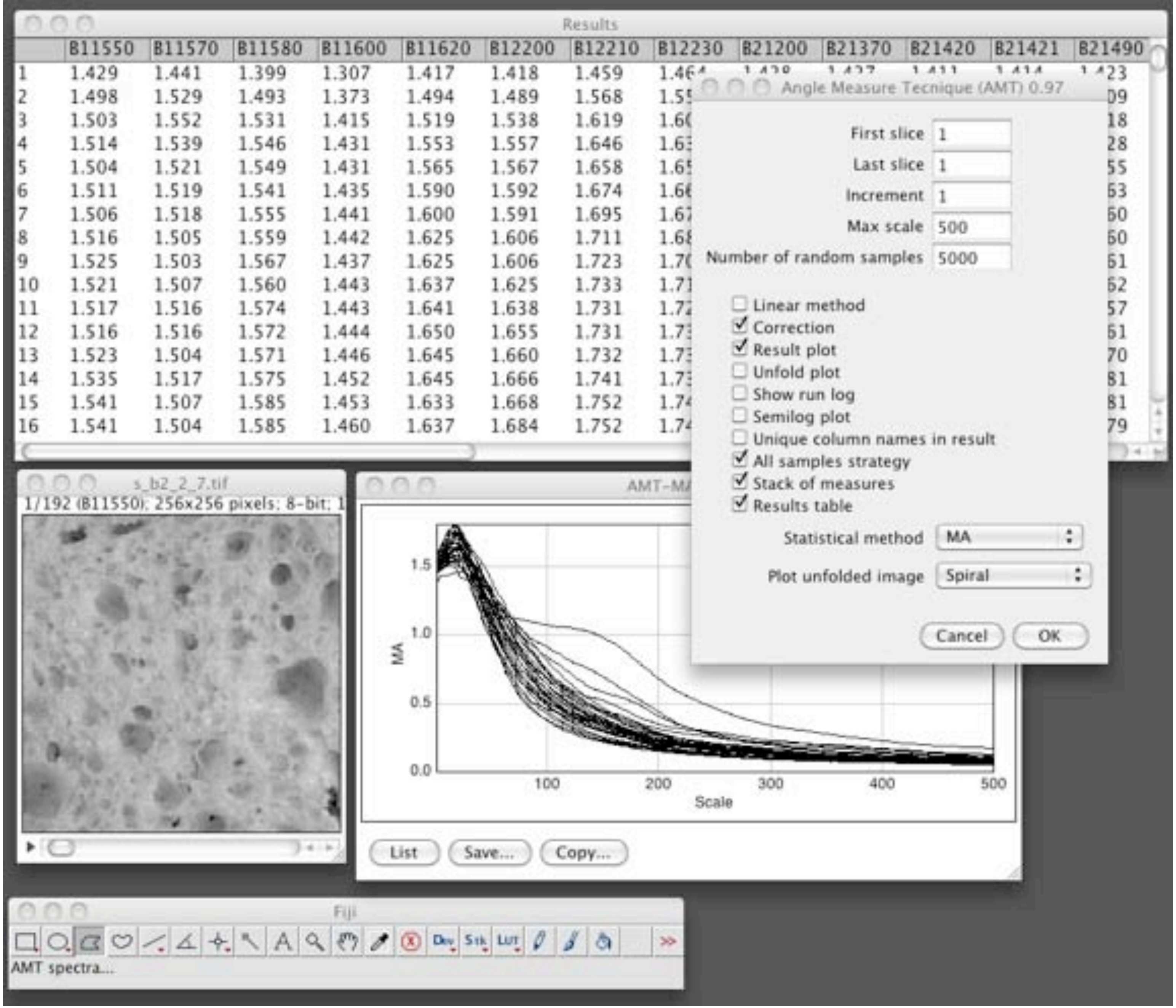

Open, save and create images
Modify and convert images, geometric operations
Statistical measurements, histograms, plotting
ImageJ
File Edit Image Process Analyze Plugins Window Help
Version 1.36b (275 commands, 18 macros)
Editing images, drawing operations
Point and arithmetic operations, filters
Managing plugins


Plugin
Plugin
Plugin
Plugin
Plugin
ImageJ
AWT
Java Core


ImageCanvas
(java.awt.Canvas)
ImageWindow
(java.awt.Frame)
java.awt.Image
ImagePlus
win
img
ip
stack
fileInfo
file, URL
ImageProcessor
pixels
pixel array
ImageStack
stack
slice 1
slice 2
slice 3
slice 4
slice N

Plugin: Invert image

```
import ij.ImagePlus;
import ij.plugin.filter.PlugInFilter;
import ij.process.ImageProcessor;

public class My_Inverter implements PlugInFilter {

        public int setup(String arg, ImagePlus im) {
                return DOES_8G; // this plugin accepts 8-bit grayscale images
        }

        public void run(ImageProcessor ip) {
                int w = ip.getWidth();
                int h = ip.getHeight();

                // iterate over all image coordinates
                for (int u = 0; u < w; u++) {
                        for (int v = 0; v < h; v++) {
                                int p = ip.getPixel(u, v);
                                ip.putPixel(u, v, 255-p);
                        }
                }
        }

}
```



Results
B11550 B11570 B11580 B11600 B11620 B12200 B12210 B12230 B21200 B21370 B21420 B21421 B21490
1 1.429 1.441 1.399 1.307 1.417 1.418 1.459
2 1.498 1.529 1.493 1.373 1.494 1.489 1.568
3 1.503 1.552 1.531 1.415 1.519 1.538 1.619
4 1.514 1.539 1.546 1.431 1.553 1.557 1.646
5 1.504 1.521 1.549 1.431 1.565 1.567 1.658
6 1.511 1.519 1.541 1.435 1.590 1.592 1.674
7 1.506 1.518 1.555 1.441 1.600 1.591 1.695
8 1.516 1.505 1.559 1.442 1.625 1.606 1.711
9 1.525 1.503 1.567 1.437 1.625 1.606 1.723
10 1.521 1.507 1.560 1.443 1.637 1.625 1.733
11 1.517 1.516 1.574 1.443 1.641 1.638 1.731
12 1.516 1.516 1.572 1.444 1.650 1.655 1.731
13 1.523 1.504 1.571 1.446 1.645 1.660 1.732
14 1.535 1.517 1.575 1.452 1.645 1.666 1.741
15 1.541 1.507 1.585 1.453 1.633 1.668 1.752
16 1.541 1.504 1.585 1.460 1.637 1.684 1.752
Angle Measure Tecnique (AMT) 0.97
First slice 1
Last slice 1
Increment 1
Max scale 500
Number of random samples 5000
Linear method
Correction
Result plot
Unfold plot
Show run log
Semilog plot
Unique column names in result
All samples strategy
Stack of measures
Results table
Statistical method MA
Plot unfolded image Spiral
Cancel
OK
s_b2_2_7.tif
1/192 (B11550); 256x256 pixels; 8-bit;
MA
1.5
1.0
0.5
0.0
100
200
300
400
500
Scale
List
Save...
Copy...
Fiji
AMT spectra...

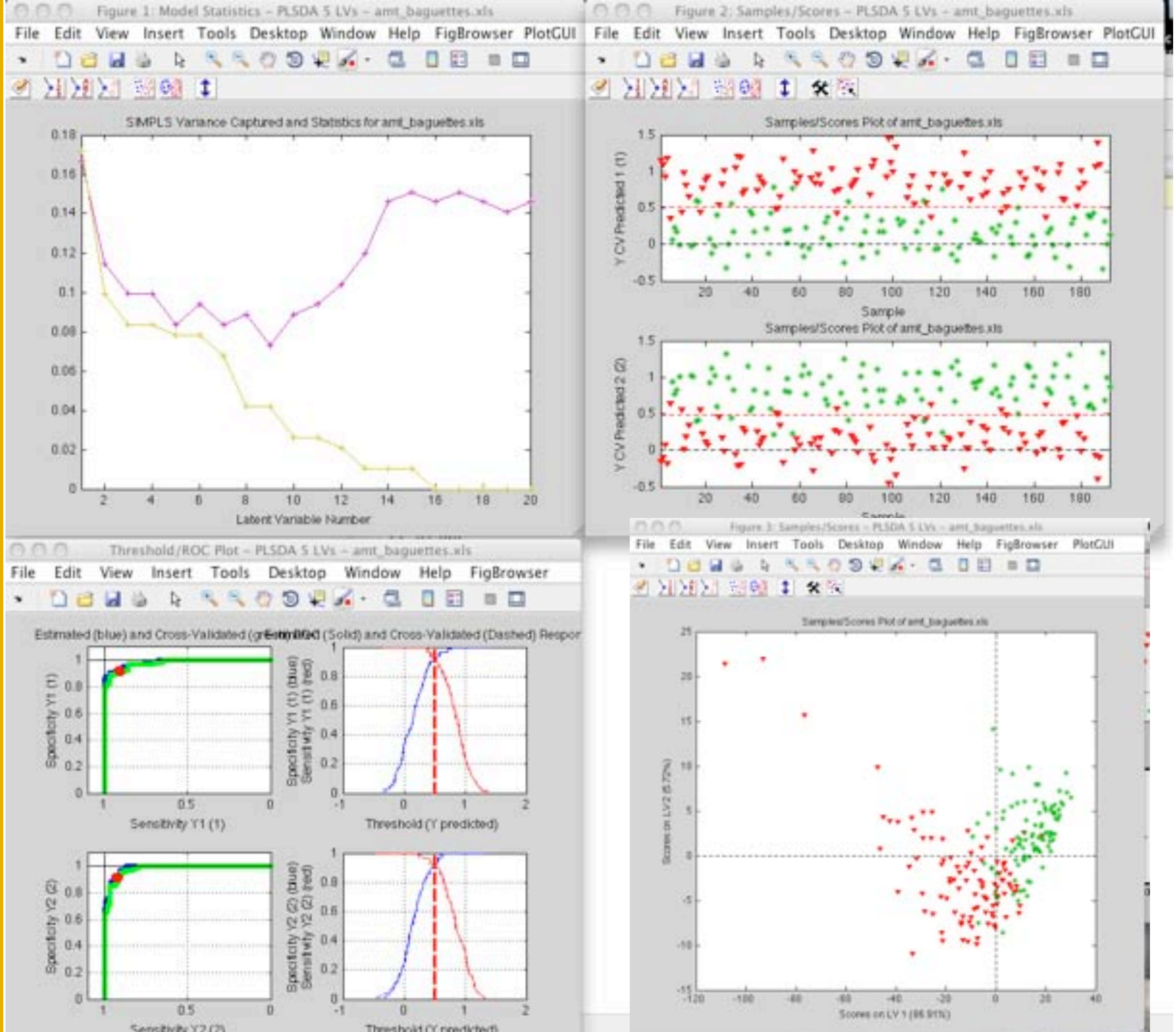
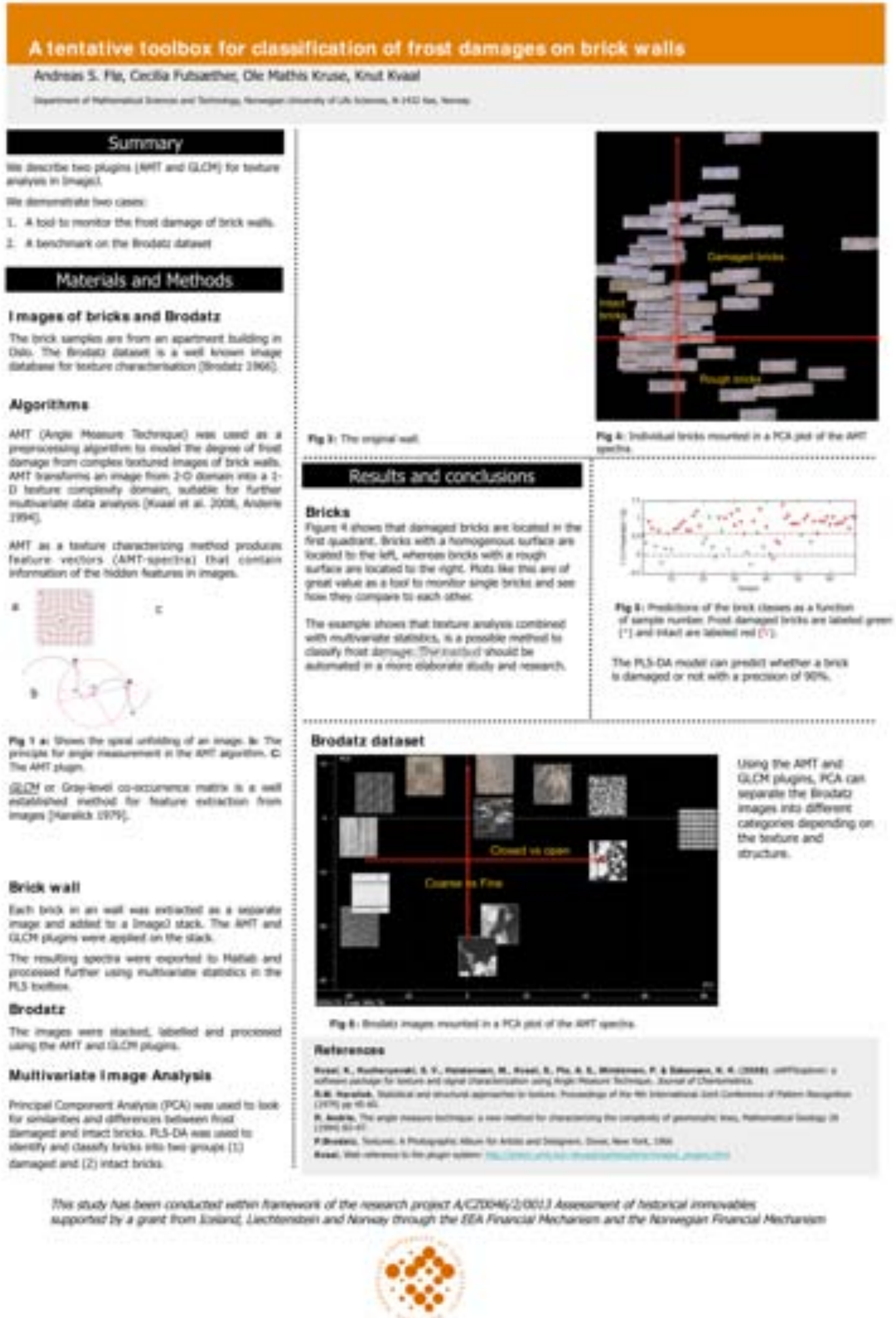


Figure 1: Model Statistics – PLSDA 5 LVs – amt_baguettes.xls
SIMPLS Variance Captured and Statistics for amt_baguettes.xls
Latent Variable Number
Figure 2: Samples/Scores – PLSDA 5 LVs – amt_baguettes.xls
Samples/Scores Plot of amt_baguettes.xls
Y CV Predicted 1 (1)
Sample
Y CV Predicted 2 (2)
Threshold/ROC Plot – PLSDA 5 LVs – amt_baguettes.xls
Specificity Y1 (1)
Sensitivity Y1 (1)
Specificity Y1 (1) (blue)
Sensitivity Y1 (1) (red)
Threshold (Y predicted)
Specificity Y2 (2)
Specificity Y2 (2) (blue)
Sensitivity Y2 (2) (red)
Figure 3: Samples/Scores – PLSDA 5 LVs – amt_baguettes.xls
Samples/Scores Plot of amt_baguettes.xls
Scores on LV 2 (6.72%)
Scores on LV 1 (86.91%)

Progress

- The plugins have been established and published globally
  - http://arken.umb.no/~kkvaal/eamtexplorer/imagej_plugins.html
- The plugin system is a part of the software toolkit for the research project A/CZ0046/2/
- Next: Matlab replacements

A tentative toolbox for classification of frost damages on brick walls



A tentative toolbox for classification of frost damages on brick walls

Andreas S. Flø, Cecilia Futsaether, Ole Mathis Kruse, Knut Kvaal

Summary

We describe two plugins (AMT and GLCM) for texture analysis in ImageJ.

We demonstrate two cases:

1. A tool to monitor the frost damage of brick walls.
2. A benchmark on the Brodatz dataset

Materials and Methods

Images of bricks and Brodatz

The brick samples are from an apartment building in Oslo. The Brodatz dataset is a well known image database for texture characterisation (Brodatz 1966).

Algorithms

AMT (Angle Measure Technique) was used as a preprocessing algorithm to model the degree of frost damage from complex textured images of brick walls. AMT transforms an image from 2-D domain into a 1-D texture complexity domain, suitable for further multivariate data analysis (Kvaal et al. 2008, Andrle 1994).

AMT as a texture characterizing method produces feature vectors (AMT-spectra) that contain information of the hidden features in images.

Fig 1 a: Shows the spiral unfolding of an image. b: The principle for angle measurement in the AMT algorithm. C: The AMT plugin.

GLCM or Gray-level co-occurrence matrix is a well established method for feature extraction from images (Haralick 1979).

Brick wall

Each brick in an wall was extracted as a separate image and added to a ImageJ stack. The AMT and GLCM plugins were applied on the stack.

The resulting spectra were exported to Matlab and processed further using multivariate statistics in the PLS toolbox.

Brodatz

The images were stacked, labelled and processed using the AMT and GLCM plugins.

Multivariate Image Analysis

Principal Component Analysis (PCA) was used to look for similarities and differences between frost damaged and intact bricks. PLS-DA was used to identify and classify bricks into two groups (1) damaged and (2) intact bricks.

Fig 3: The original wall.

Fig 4: Individual bricks mounted in a PCA plot of the AMT spectra.

Results and conclusions

Bricks

Figure 4 shows that damaged bricks are located in the first quadrant. Bricks with a homogenous surface are located to the left, whereas bricks with a rough surface are located to the right. Plots like this are of great value as a tool to monitor single bricks and see how they compare to each other.

The example shows that texture analysis combined with multivariate statistics, is a possible method to classify frost damage. The method should be automated in a more elaborate study and research.

Fig 5: Predictions of the brick classes as a function of sample number. Frost damaged bricks are labeled green (*) and intact are labeled red (*).

The PLS-DA model can predict whether a brick is damaged or not with a precision of 90%.

Brodatz dataset

Using the AMT and GLCM plugins, PCA can separate the Brodatz images into different categories depending on the texture and structure.

Fig 6: Brodatz images mounted in a PCA plot of the AMT spectra.

References

Kvaal, K., ... (2008) ...

R.M. Haralick, Statistical and structural approaches to texture, Proceedings of the 4th International Joint Conference of Pattern Recognition (1979) pp 45-60.

R. Andrle, The angle measure technique: a new method for characterizing the complexity of geomorphic lines, Mathematical Geology 26 (1994) 83-97.

P.Brodatz, Textures: A Photographic Album for Artists and Designers, Dover, New York, 1966

Kvaal, Web reference to the plugin system: ...

This study has been conducted within framework of the research project A/CZ0046/2/0013 Assessment of historical immovables supported by a grant from Iceland, Liechtenstein and Norway through the EEA Financial Mechanism and the Norwegian Financial Mechanism

Summary

- We describe two plugins (AMT and GLCM) for texture analysis in ImageJ.
- We demonstrate one case:

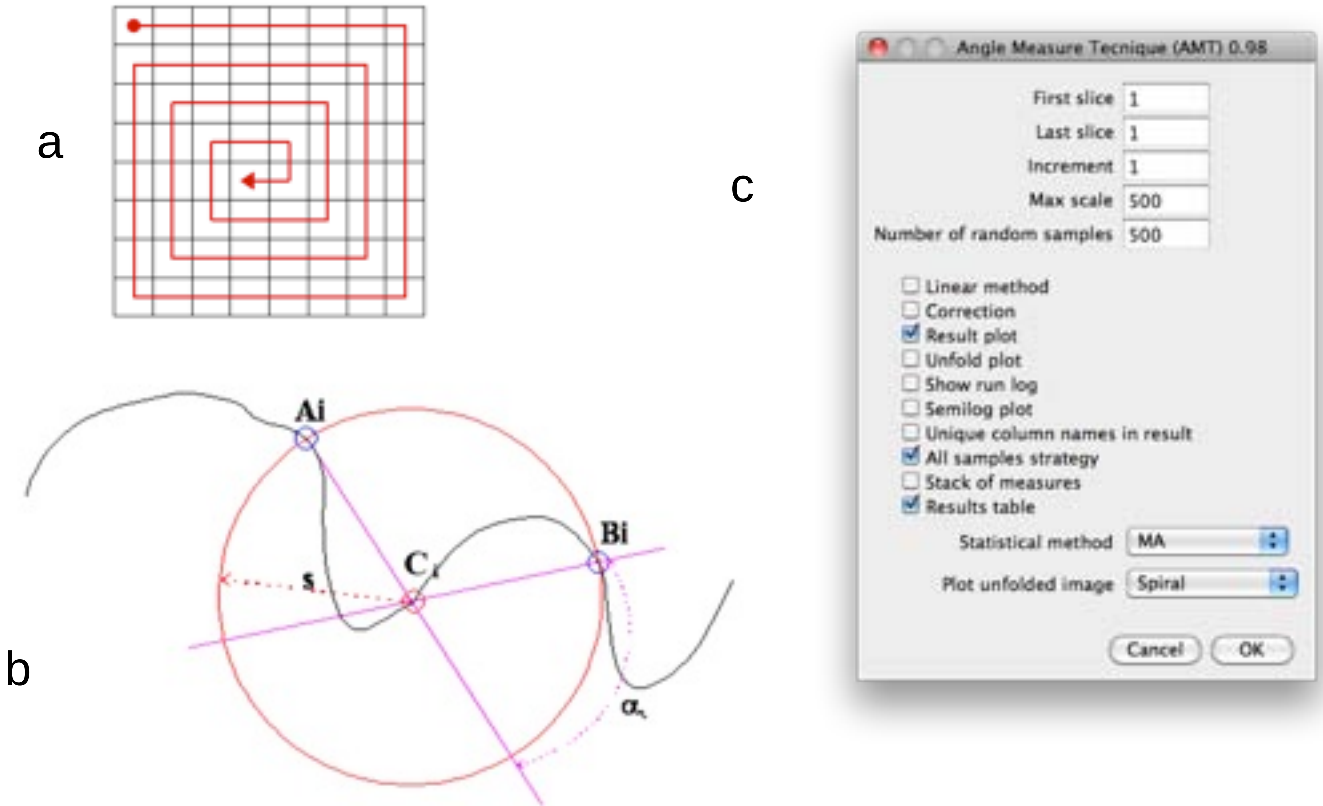
1. A tool to monitor the frost damage of brick walls

Materials and methods

- Images of bricks from a selected building
- The brick samples are from an apartment building in Oslo.

Algorithms

- AMT (Angle Measure Technique) was used as a preprocessing algorithm to model the degree of frost damage from complex textured images of brick walls. AMT transforms an image from 2-D domain into a 1-D texture complexity domain, suitable for further multivariate data analysis [Kvaal et al. 2008, Andrle 1994].
- AMT as a texture characterizing method produces feature vectors (AMT-spectra) that contain information of the hidden features in images.



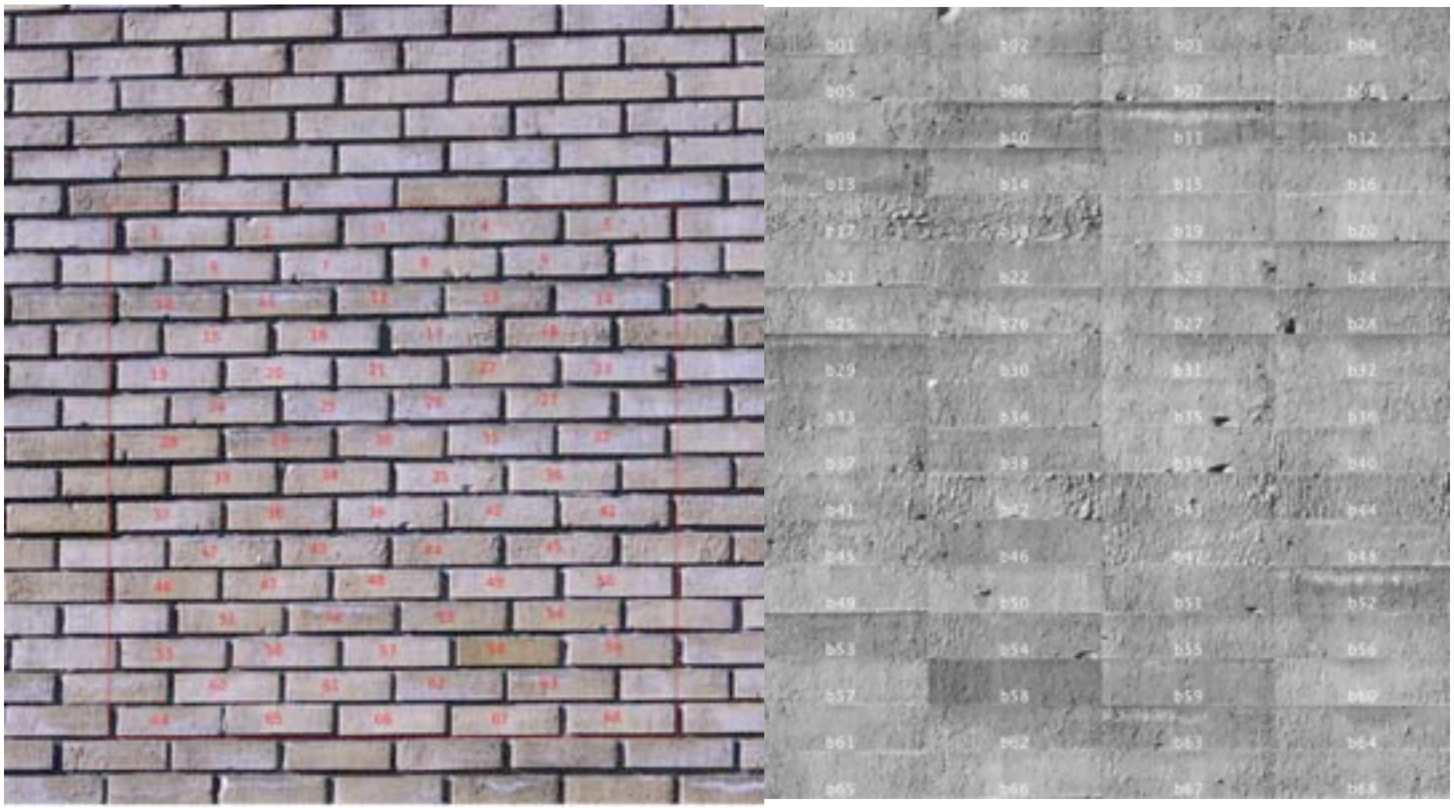
a: Shows the spiral unfolding of an image. **b:** The principle for angle measurement in the AMT algorithm. **C:** The AMT plugin GUI.

Brick Wall

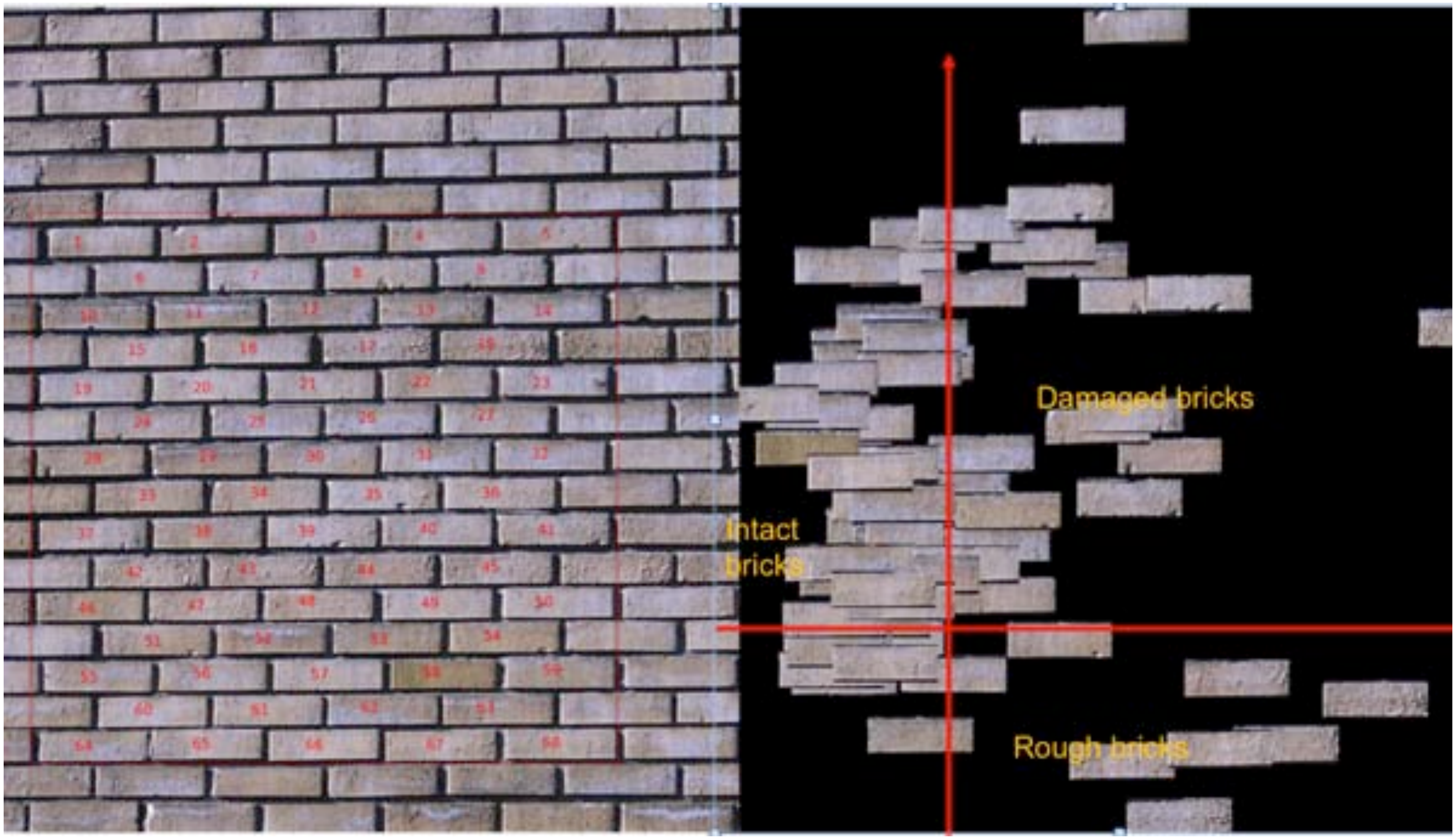
- Each brick in wall wall was extracted as a separate image and added to a ImageJ stack. The AMT and GLCM plugins were applied on the stack.
- The resulting spectra were exported to Matlab and processed further using multivariate statistics in the PLS toolbox.

Stavangergata 3

Brick Samples as separate objects



Bricks selection and AMT PCA scores



Classification of damage

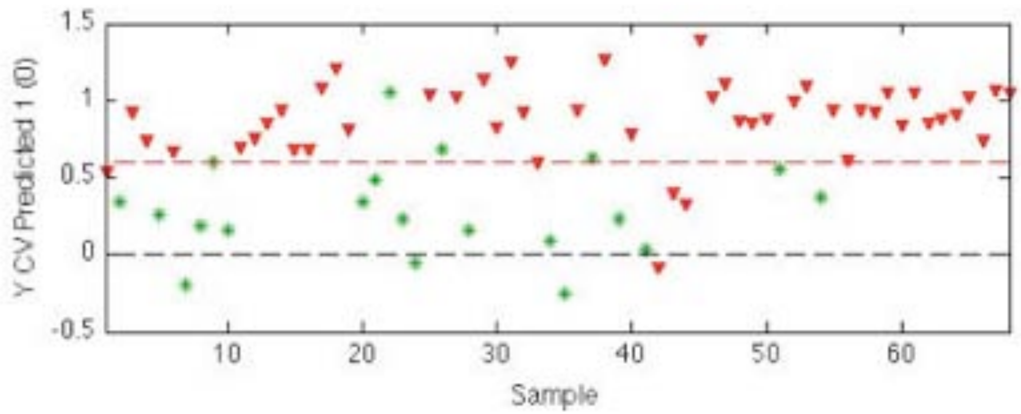


Fig 5: Predictions of the brick classes as a function of sample number. Frost damaged bricks are labeled green (*) and intact are labeled red (▽).

The PLS-DA model can predict whether a brick is damaged or not with a precision of 90%.

Quick monitoring of damage

- Damaged bricks are located in the first quadrant. Bricks with a homogenous surface are located to the left, whereas bricks with a rough surface are located to the right.
- Plots like this are of great value as a tool to monitor single bricks and see how they compare to each other.
- Texture analysis combined with multivariate statistics (PCA MAP), is a possible method to classify frost damage. The method should be automated in a more elaborate study and research.

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References

- Kvaal, K., Kucheryavski, S. V., Halstensen, M., Kvaal, S., Flo, A. S., Minkkinen, P. & Esbensen, K. H. (2008). eAMTexplorer: a software package for texture and signal characterization using Angle Measure Technique. Journal of Chemometrics.
- R.M. Haralick, Statistical and structural approaches to texture. Proceedings of the 4th International Joint Conference of Pattern Recognition (1979) pp 45-60.
- R. Andrle, The angle measure technique: a new method for characterizing the complexity of geomorphic lines, Mathematical Geology 26 (1994) 83–97.
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- Kvaal, Web reference to the plugin system: http://arken.umb.no/~kkvaal/eamtexplorer/imagej_plugins.html