Medical Image Computing

Exercise 02

Master Medical Technologies

3. Semester

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1 Image texture descriptors

1.1 Load the image

For this exercise the document *breastXray.tif*, shown in figure (Fig.1.1) was provided. The image has a size of 560 times 480 pixels, hence there are 672 blocks/regions with the size of 20x20 pixels, which would be arranged in the format of 28x24 blocks. These blocks will be used for all further steps.

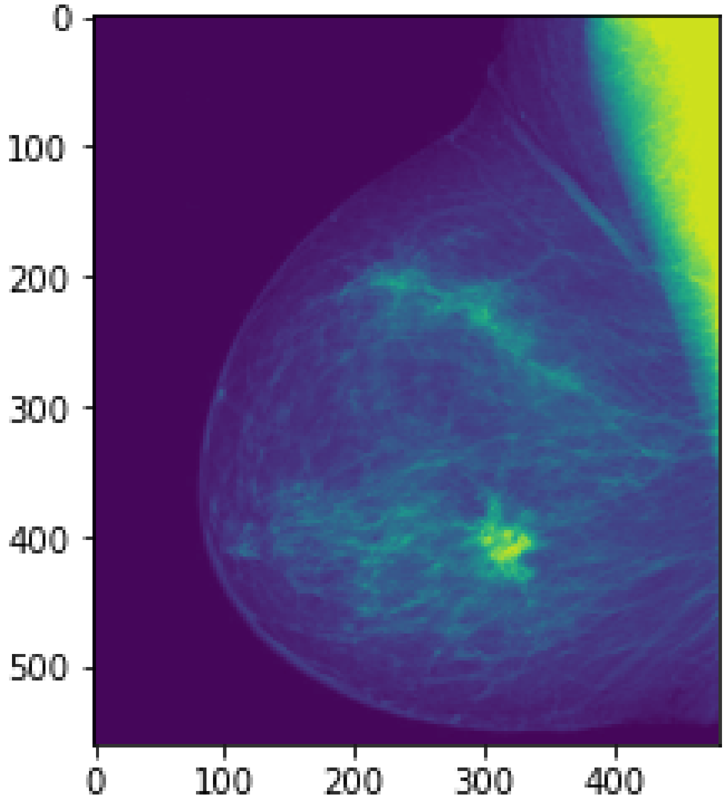


Fig. 1.1: Original X-Ray Image of a breast.

1.2 Determine the gray level co-occurrence matrix (GLCM)

For the next step, the GLCM will be determined for each of the 672 blocks. The GLCM is supposed to examine the spatial relationship among pixels and defines how frequently a combination of pixels are present in an image in a given direction (0°, 45°, 90° and 135° Degrees) and distance D (D=1). The function "greycomatrix" allows to defining the region, distance, angles and levels. The number of grey levels is set to 16. The size of the GLCM is 16x16x1x4. Consisting of levels x levels x number of distances x number of angles. The GLCM is determined for each of the 672 blocks and saved together with the block format of 28x24.

1.3 Calculate the correlation, contrast, energy and homogeneity

For each of the prior generated GLCMs the four features correlation, contrast, energy and homogeneity are calculated, leading to 16 images with the four textures and four directions defined in the previous step (Fig.1.2). The first row of images depicts the correlation at different degrees. Correlation is the measurement of how correlated a pixel is to its neighbor over the entire image. Here the possible pixel errors in the top left of the otherwise smooth background have a high impact on the correlation. The second row shows the contrast, a measure of intensity contrast between a pixel and its neighbors. The contrast is highest around the bright tissue of the breast in the bottom right. The contrast is overall rather low. The third row shows the energy, which is a measure of uniformity, with the highest values for constant regions. Here the outline of the breast is very well visible, the bright tissue of the breast results in lower uniformity. The last row highlights the homogeneity, the highest values are achieved in the background and the lowest similar to the energy feature are a result of the brighter tissue. The different directions produce slightly different grey values, but overall the impacts seem marginal.

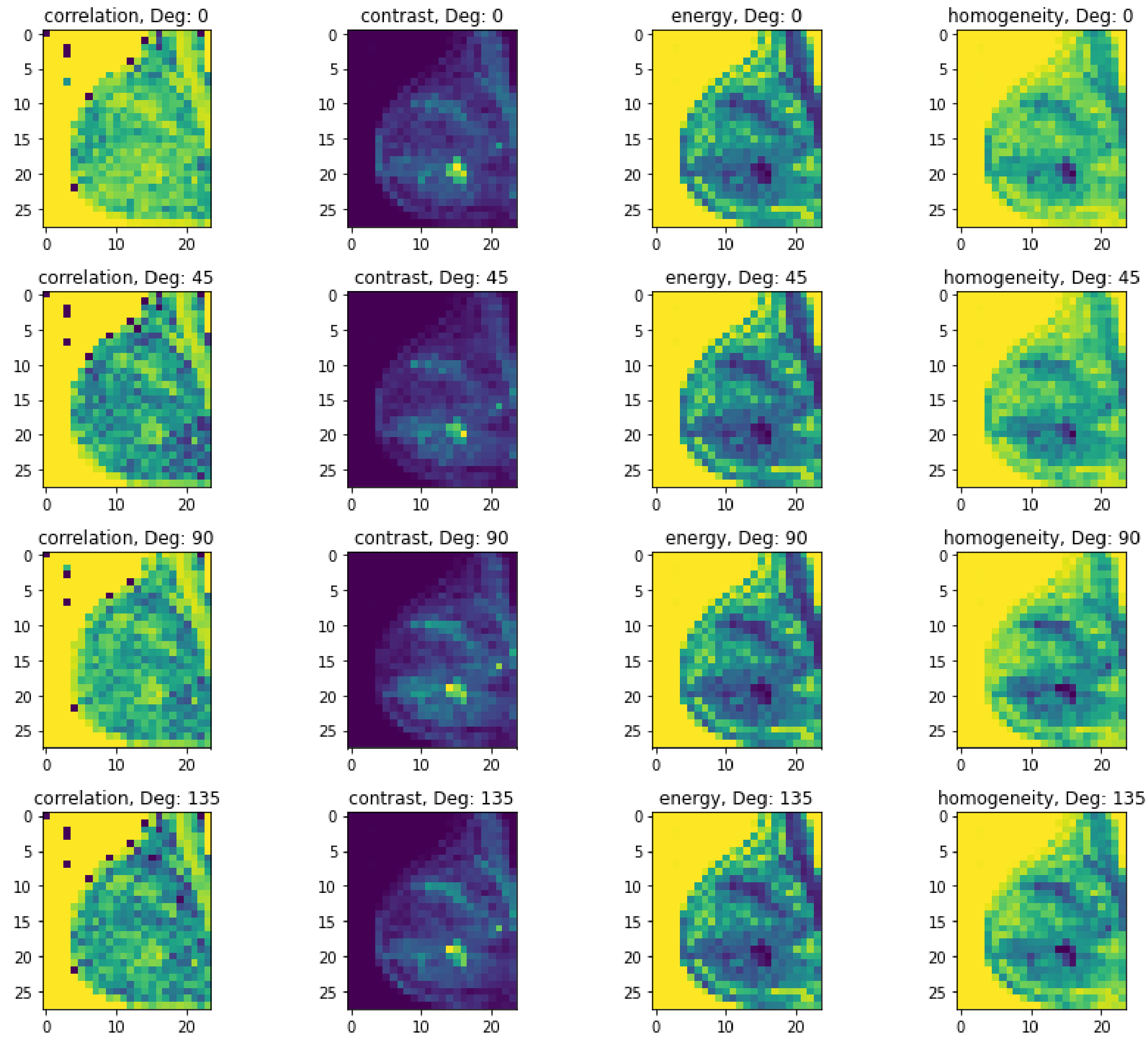


Fig. 1.2: The result of four different features correlation, contrast, energy and homogeneity at the four different directions 0°, 45°, 90° and 135° Degrees.

1.4 Build a design matrix

A design matrix based on the GCLM-blocks was the next step to create. For that, each block is an observation and the texture descriptors for each angle are the features.
To come to the desired format of a 2D-array, the block array with its 28 rows and 24 columns was flattened to a list of 672 items, where each block kept its features calculated in the previous step in section 1.3 "Calculate the correlation, contrast, energy and homogeneity". Hence the size of the created design matrix is 672 rows and 16 columns. The block number as shown in table 1.1 is not included in the design matrix and is only shown in the table for clarity.

Bl.Nr.	correlation				contrast				energy				homogeneity			
	0°	45°	90°	135°	0°	45°	90°	135°	0°	45°	90°	135°	0°	45°	90°	135°
1	-0.0013	-0.0014	-0.0026	-0.0014	0.0026	0.0028	0.0053	0.0028	0.9974	0.9972	0.9947	0.9972	0.9987	0.9986	0.9974	0.9986
2	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1
3	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1
...																
670	0.9002	0.7960	0.7903	0.7960	0.0342	0.0665	0.06842	0.0665	0.7900	0.7823	0.7810	0.7823	0.9829	0.9668	0.9658	0.9668
671	0.8097	0.6866	0.6789	0.6218	0.05263	0.08033	0.08421	0.09695	0.820	0.8183	0.8127	0.8099	0.9736	0.9598	0.9578	0.9515
672	0.9250	0.7794	0.7658	0.8061	0.03421	0.09141	0.09736	0.08033	0.7618	0.7424	0.7454	0.7487	0.9828	0.9542	0.9544	0.9598

Table 1.1: Design matrix: block x features and angles

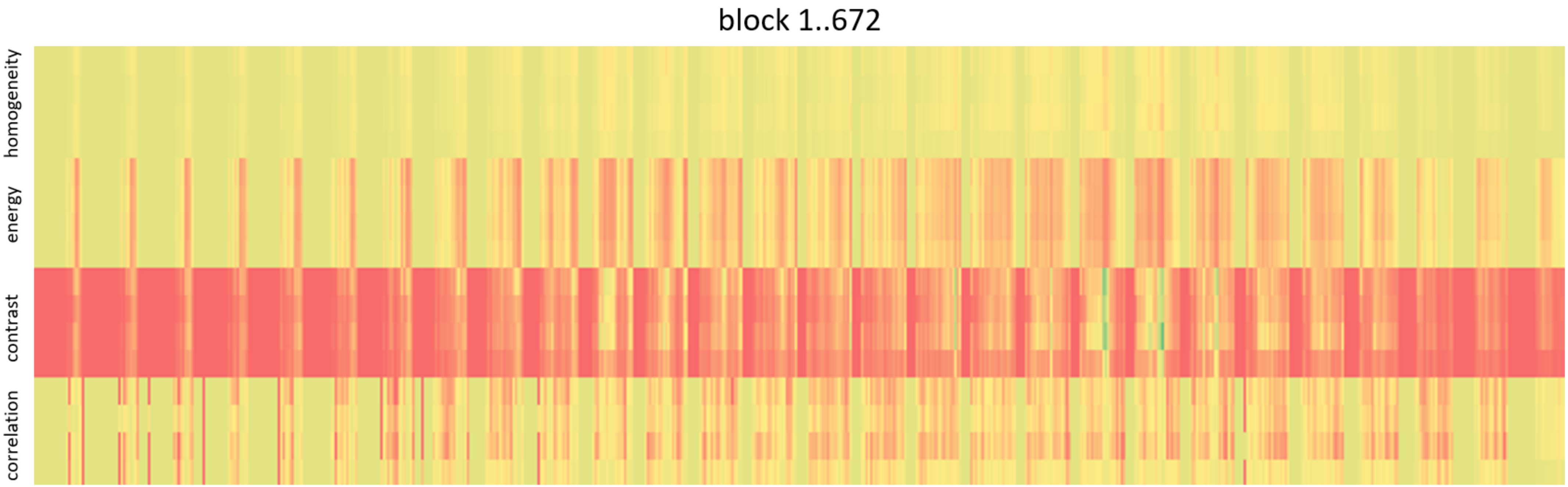


Fig. 1.4: Heatmap of the design matrix, showing the gradient of the features over the blocks.

1.5 BONUS: Try two different pixel distances

To get a better understanding, how a change of the distance parameter works out on the resulting image, the grey-level co-occurrence matrix for six different distances was calculated. The results are shown in figure 1.3.

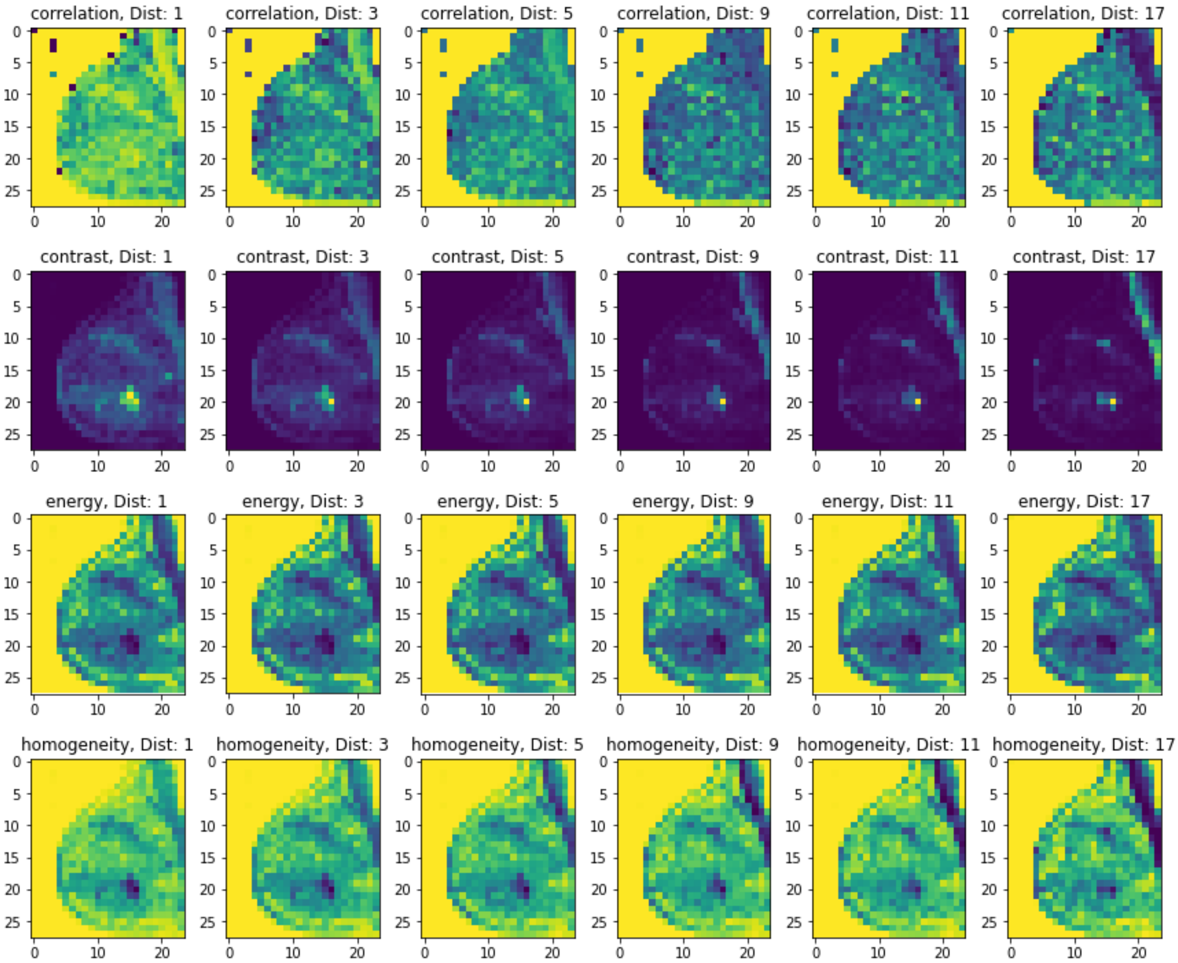


Fig. 1.3: Different values for the distance parameter and the result for the four features.

By taking a closer look at figure 1.3, the influence of the distance parameter on the different features is quite easy to see.
For correlation, the pixel-artefacts on the left upper corner vanish what would be beneficial, but at the same time, the structure would get more blurry and with the high distance of seventeen, seen on the last image in the first row, the breast tissue looks just like noise.
The acuteness of the contrast diminishes with the increase of the distance-value. With a distance-parameter of one or three the structures of the breast are still distinguishable, but with higher distances like eleven or seventeen, only the parts with the highest contrast in the original image are still noticeable.
Changing the distance parameter has no big influence on the energy-feature. It can be seen

in figure 1.3, that the whole image gets darker and that some fine structures slightly vanish. But from all four feature-parameters, the energy changed less in respect to the distance.
The last reviewed parameter concerning different distance-values is homogeneity. With a higher distance value, the transition from one colour or grey scale of the image to another gets rougher. With the small distances of one or three pixels, the transitions are very smooth but with the higher ones, like eleven or seventeen, they are quite rugged.
For the second part of the assignment, the distance value of one pixel is used. The main reason for that was a good image from the contrast feature.

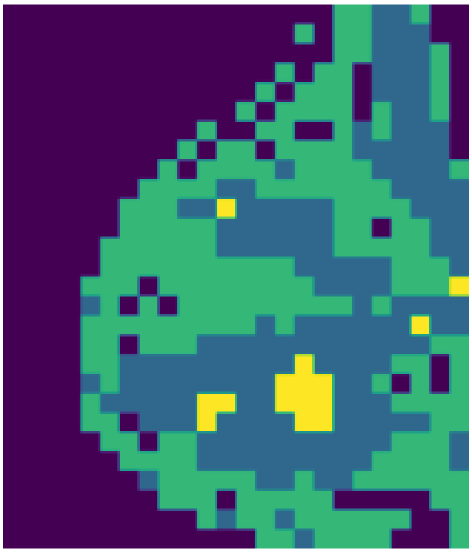
2 Texture-based clustering

2.1 Clustering superpixel using k-means clustering

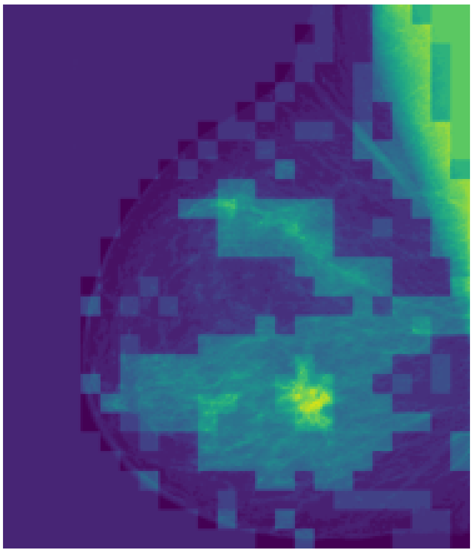
The design matrix must be 2-dimensional for using it as an input for the k-means clustering function of scikit-library. The columns represent the features the rows the observations. The position where the observation is taken is not relevant for the function. The observations get clustered according to their features. As required we set the parameter for the number of clusters to four so we get 4 labels. All other parameters were left unused, which means the default values were used. The repetition for the initialization was set to 10 by default.

2.2 Visualization and overlay to the original image

One block, which consists of 20x20 pixels, got one label from the k-means-function. Therefore each pixel in this block/region has the same label when resizing the label-image to the size of the original image. The main regions found (see Fig 2.1) are; the background (dark blue) the breast in general (light green) as well as some denser tissue (dark green). The bright, knot-like tissue is also found and marked in yellow. All regions seem to have some artefacts. The upper right corner is not in the region of interest. We found better segmentation results by not using the correlation feature. Probably because it shows little relevant information inside the region of the breast (see Figure 1.2 column 1). It also seems like the different directions have little impact on the regions, at least for the chosen length.



(a) Differentiation of the original image into four segments.



(b) Overlay of the Segments on the original image.

Fig. 2.1: Segmentation of the original image using co-occurrence matrix, calculating some of its texture properties and using this in a k-means algorithm to find different regions.

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