Project 1: IN5520

Segmentation of textured regions in an image

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Problem description

In this project we will investigate the texture analysis problem with relation to image segmentation. Analysis of texture is an important problem in image processing. Texture can be described by visual characteristics such as fine, course, smooth, blurry and by spatial repetitions of basic texture elements. Image segmentation involves the problem of dividing an image into objects of interest. Objects may be isolated from image features found from intensity (or abrupt change in intensity), similarity, discontinuity, smoothness, contrast and many more. The textures we will be analyzing are presented in Figure 1 as Mosaic 1 and Mosaic 2. These two images contains a set of eight different textures.

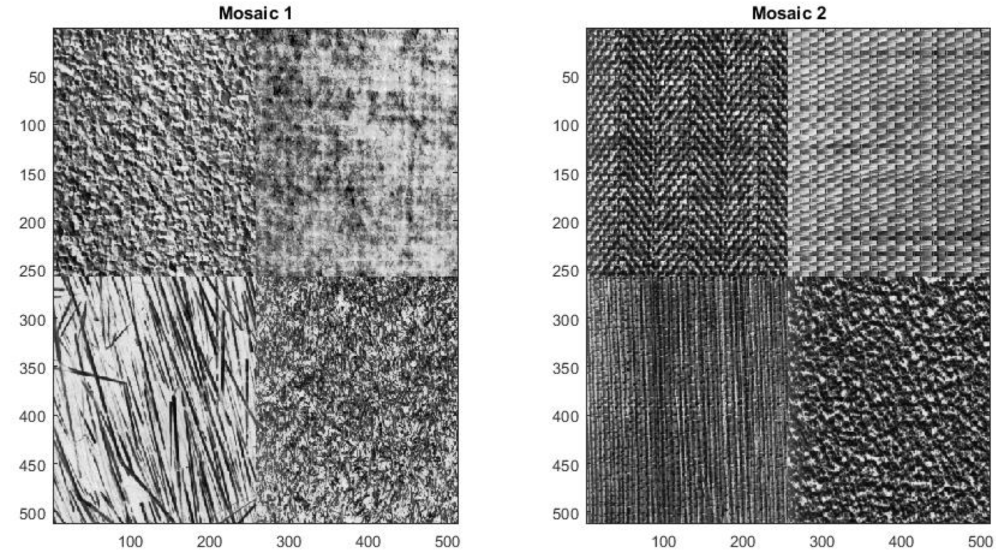


Figure 1: The eight different textures we will investigate the segmentation problem on. We can observe that the textures can be visually differentiated by their different textural characterization, such as dominant textural element direction, texture element size, coarseness etc.

Theory and methods

There exist many methods for analysis of texture in digital image processing. In this project we will be using methods such as 2D Fourier transform and first order statistics, such as mean, variance and energy in order for simple analysis. For segmentation of texture we will turn to second order statistics by computing inverse difference moment (IDM), contrast (also known as inertia) and cluster shade from the gray level co-occurrence matrix (GLCM). The 2D discrete Fourier transform (DFT) of a function $f(x, y)$ is given by the equation

$$F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(\frac{ux}{M}+\frac{vy}{N})}$$

where (u, v) determine the frequency of the function. The transformation into the frequency domain could provide details about the frequency content and orientation of textural elements within the images. For a first order statistics measure we can use variance, which is a measure of roughness of the image. The variance is defined as

$$\sigma^2 = \sum_{i=0}^{G-1} (i-\mu)^2 P(i)$$

where i is the gray-levels of the image, μ is the mean and $P(i)$ is the normalized histogram values. A histogram of a digital image is defined in the gray-level range $[0, G-1]$, and by the discrete function $h(r_k) = n_k$ where r_k is the intensity level and k is the number of intensity levels. From this we get the normalized values

$$P(i) = \frac{h(r_k)}{n}$$

where n is the numbers of pixels in the image. From probability theory we can refer to the normalized histogram values as an estimation of probability of intensity r_k. Another first order statistic, which gives a measure of homogeneity of the image, is the energy function. Energy of an image is defined as

$$E = \sum_{i=0}^{G-1} [P(i)]^2$$

For computing second order statistics we turn to the computation of the GLCM, which is a measure of intensity change from one pixel to a neighboring pixel. The neighboring pixel, could be defined at a distance of choice, but in this project a distance of 1 pixel was used for computations. The co-occurrence matrix estimates the joint probability of going from a gray level to another. This could be measured along a given direction. The notation of the GLCM is dependent on distance and the direction its measured. The joint probability of the GLCM is defined as

$$P(i, j|\Delta x, \Delta y) = WQ(i, j|\Delta x, \Delta y)$$

where

$$W = \frac{1}{(M-\Delta x)(N-\Delta y)} \quad , \quad Q(i, j|\Delta x, \Delta y) = \sum_{n=1}^{N-\Delta y} \sum_{m=1}^{M-\Delta x} A$$

where

$$A = \begin{cases} 1 & \text{if } f(m,n) = i \text{ and } f(m+\Delta x, n+\Delta y) = j \\ 0 & \text{else} \end{cases}$$

From the GLCM a number of different features can be computed. In this project we focused on three different GLCM features, such as IDM, contrast and cluster shade. The IDM feature is defined as

$$\mathrm{IDM} = \sum_{i=0}^{G-1} \sum_{i=0}^{G-1} \frac{1}{1+(i-j)^2} P(i)$$

and the contrast feature as

$$\mathrm{Con} = \sum_{i=0}^{G-1} \sum_{i=0}^{G-1} (i-j)^2 P(i)$$

and the cluster shade as

$$\mathrm{CSH} = \sum_{i=0}^{G-1} \sum_{i=0}^{G-1} \left(i+j-\mu_x-\mu_y\right)^3 P(i)$$

where μ_x is the mean in the x direction and μ_y is the mean in the y direction. These features are commonly computed within a sliding window of a particular size.

Texture analysis

We start a analyzing the textures separately. The different textures are displayed in Figure 2. A visual description of the different textures are given. Analysis of the texture images were given using computation of the different features explained in the theory and methods section. These includes features such as 2D spatial frequency and first order statistics such as energy and variance. The computed features are displayed in Figure 3.

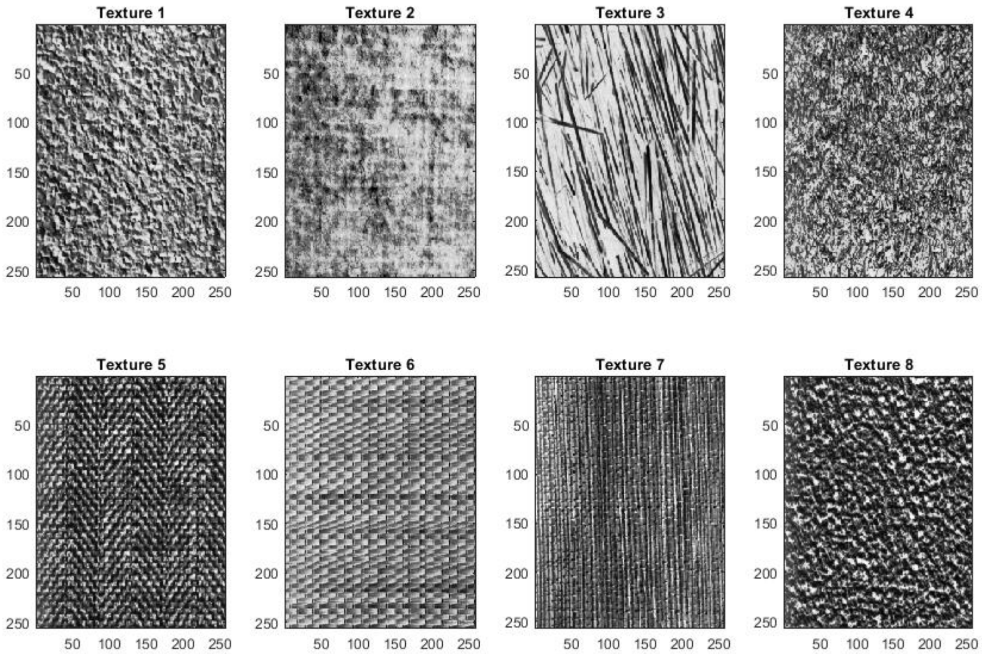


Figure 2: The two images in Figure 1, divided into the eight different textures. We can see that the different textures differs in both dominant direction texture characteristics and texture element size. Texture 3 has a clear sub-vertical dominant direction with elongated textural elements. Texture 5 and 6 has more grid like characteristic displaying angled repeated elements, and horizontal and vertical repeated textural elements respectively. Texture 1, 2, 4 and 8 displays a more random characteristic texture. Texture 7 display a vertical dominant direction with elongated textural elements.

We observe from Figure 2 and 3 that the different textures differs in both dominant direction texture characteristics, texture element size other texture characteristic such as homogeneity. Texture 3 display a sub-vertical dominant direction with elongated textural elements and areas of homogeneity. Texture 5 and 6 has more grid like characteristic displaying repeated small-sized texture elements, in addition to angled (texture 5), horizontal and vertical (texture 6) repeated textural elements. Texture 5 and 6 also show dominant direction in the vertical and horizontal direction based on the frequency content is concentrated along the vertical and horizontal axis. From Figure 2 texture 1, 2, 4 and 8 displays a more random characteristic texture. However, in Figure 3 we observe from the variance computations that texture 8 consists of sub-circular texture elements. Texture 7 display a vertical dominant direction with elongated textural elements.

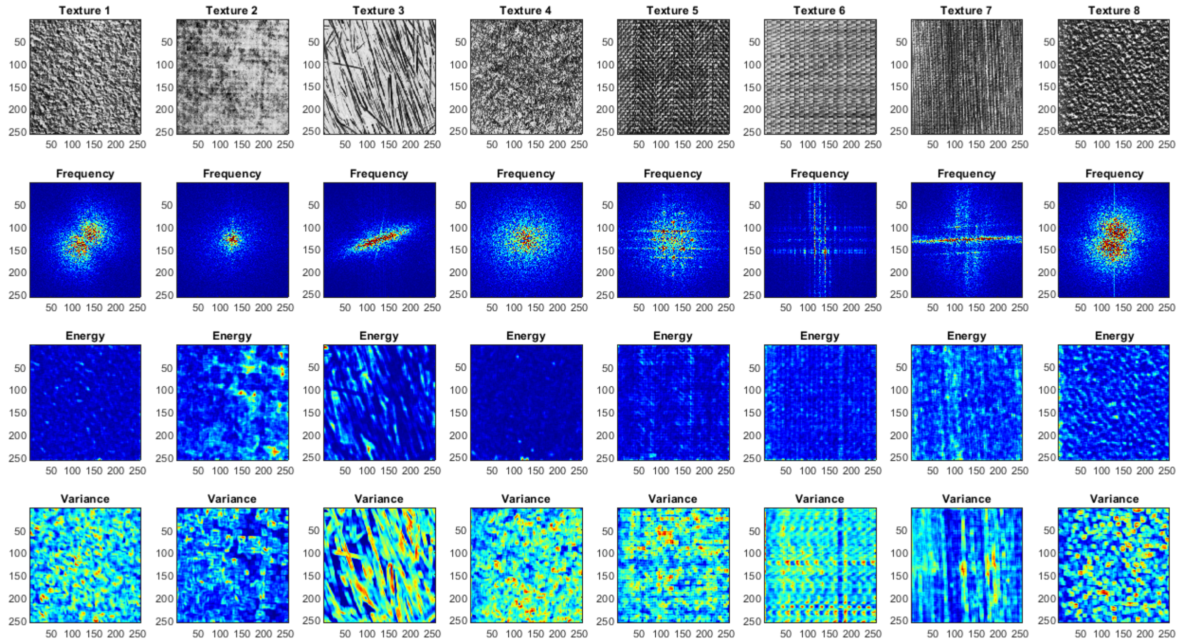
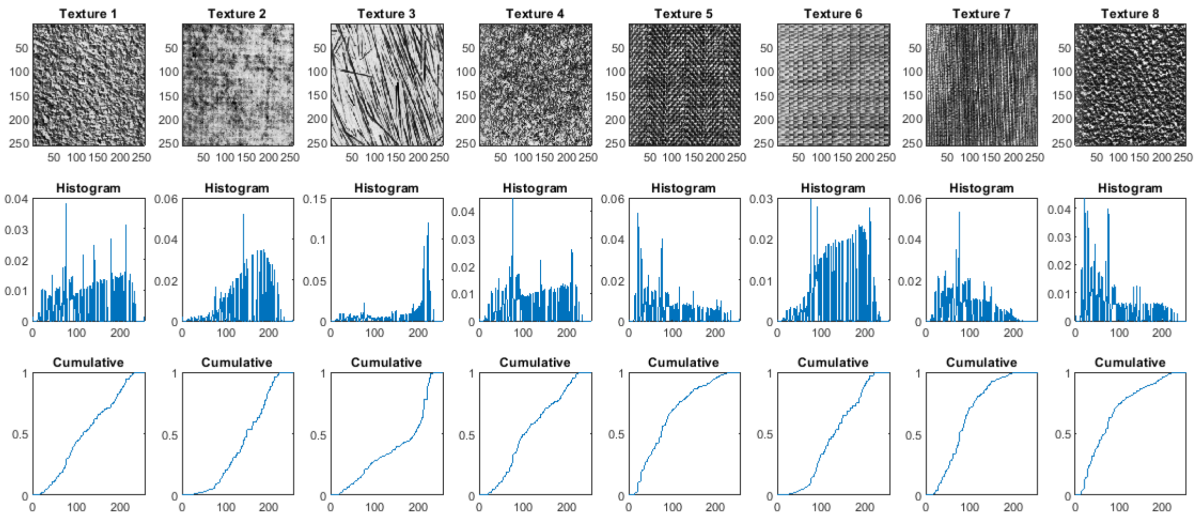


Figure 3: The eight different textures with their corresponding features frequency, energy and variance. All textures shows different characterization dependent on these features. We can observe that texture 3, 5, 6 and 7 has dominant direction based on their 2D spatial frequency content, where texture 3 shows a sub vertical dominant direction due to the frequency content is concentrated and slightly angled relative to the horizontal axis, and the others are concentrated along the horizontal and vertical axis. From the energy con Texture 1, 4, 5 and 6 shows more

Before analyzing the textures using GLCM computations, the textures are preprocessed using histogram equalization and requantization to reduce the number of gray-levels. As observed in Figure 4, the intensity levels for each texture varies. Histogram equalization was applied in order to give the textures a more uniform distribution of the intensity levels. Textures with their corresponding histograms and cumulative histograms after histogram equalization are displayed in Figure 5. We can see that after the transformation that the textures have linear CDF and a more uniform distribution in intensity levels.



more uniform, histogram equalization is applied.

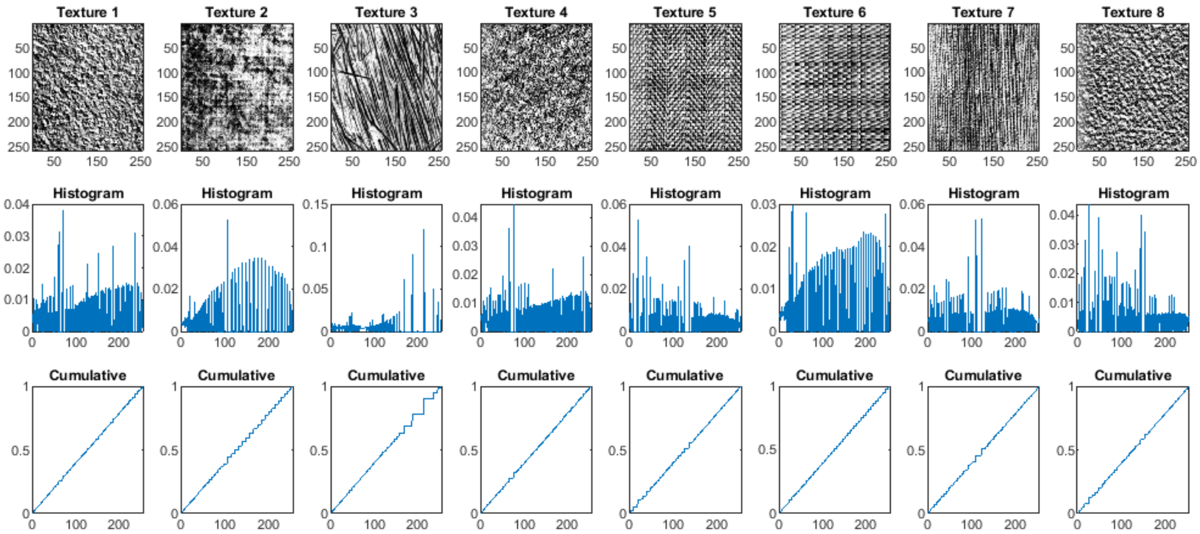


Figure 5: Textures with their corresponding histograms and cumulative histograms after histogram equalization. We can see that after the transformation that the textures have linear CDF and a more uniform distribution in intensity levels. Because of this all textures shows a similar contrast level.

After histogram equalization and gray-level requantization to 16 gray-levels, the GLCM matrices were computed based on the texture element dominant direction interpreted from the texture analysis. The histogram equalized textures and their corresponding GLCM matrices are displayed in Figure 6. All of the GLCM matrices where computed using a pixel offset of 1. The GLCM matrices for texture 1, 2, 4 and 8 was therefore computed using the isotropic GLCM. This was done by averaging all the pairwise relationships of $P(\theta)$ where $\theta \in \{0,45,90,135\}$. The texture 3 GLCM matrix was computed by averaging $\theta \in \{0,135\}$ due to the sub-vertical characteristic of the texture elements. Texture 5 and 6 GLCM matrix were computed by averaging $\theta \in \{0,90\}$ due to their vertical and horizontal characteristic of the texture elements, and texture 7 GLCM was computed using only $\theta \in \{0\}$.

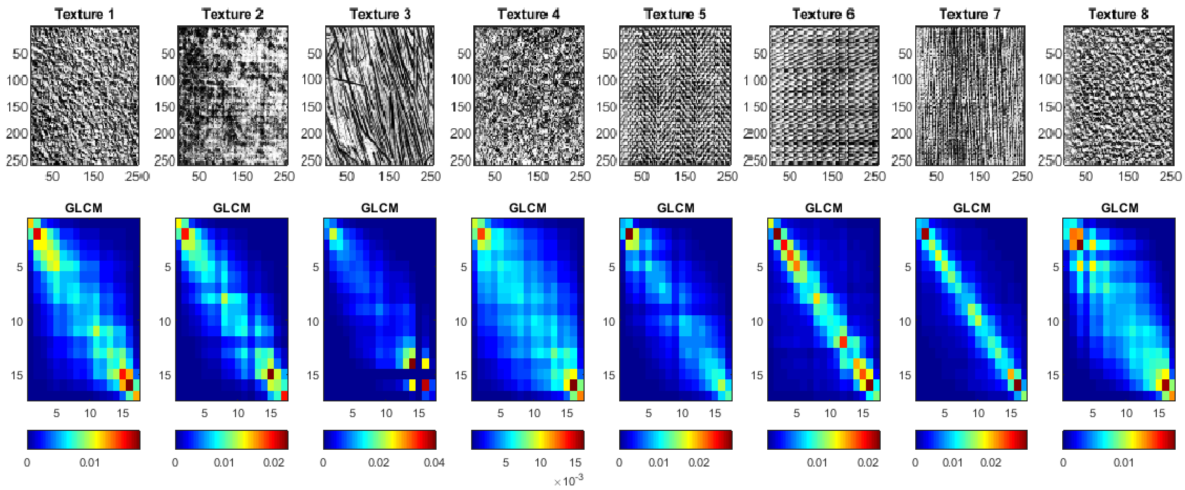


Figure 6: Histogram equalized textures with their corresponding GLCM matrices. The GLCM matrices were computed based on their texture element dominant direction, which was based on the texture analysis from visual perception and their frequency, energy and variance computations. The GLCM matrices for texture 1, 2, 4 and 8 was computed using the isotropic GLCM, by averaging all the pairwise relationships of $P(\theta)$ where $\theta \in \{0,45,90,135\}$. The texture 3 GLCM matrix was computed by averaging $\theta \in \{0,135\}$ due to the sub-vertical characteristic of the texture elements. The texture 5 and 6 GLCM matrix was computed by averaging $\theta \in \{0,90\}$ due to the vertical and horizontal characteristic of the texture elements, and texture 7 GLCM was computed using only $\theta \in \{0\}$.

The GLCM matrices both similar and different characteristics. All matrices has their values concentrated (more or less) along the diagonal, however, some more strict than other. Texture 6 and texture 7 has a very strict concentration along the diagonal, which means that the GLCM computation has captured second order statistics of similar pixel values. In this case, it could be difficult to discriminate between texture 6 and texture 7. Both textures also have highest probability consecrated at of high and low values, which makes it even more difficult to discriminate between them. However, they should be good for discriminating from the other textures. Texture 3 and texture 5 could be discriminated between by the difference in concentration into high probability at high values and high probability at low values respectively.

The GLCM features such as contrast, IDM and cluster shade were computed using a sliding window of size 31 and padding with mirror indexing, and using the same GLCM matrix computations as presented in Figure 6. The results from the GLCM feature computations are presented in Figure 7. From the feature images, we can see that contrast could be a good feature for segmentation of texture 3, texture 4, texture 5 and texture 8. IDM seem to be a suitable choice for texture 3, texture 4, texture 5 and texture 8. Cluster shade could be a possible choice for texture 4.

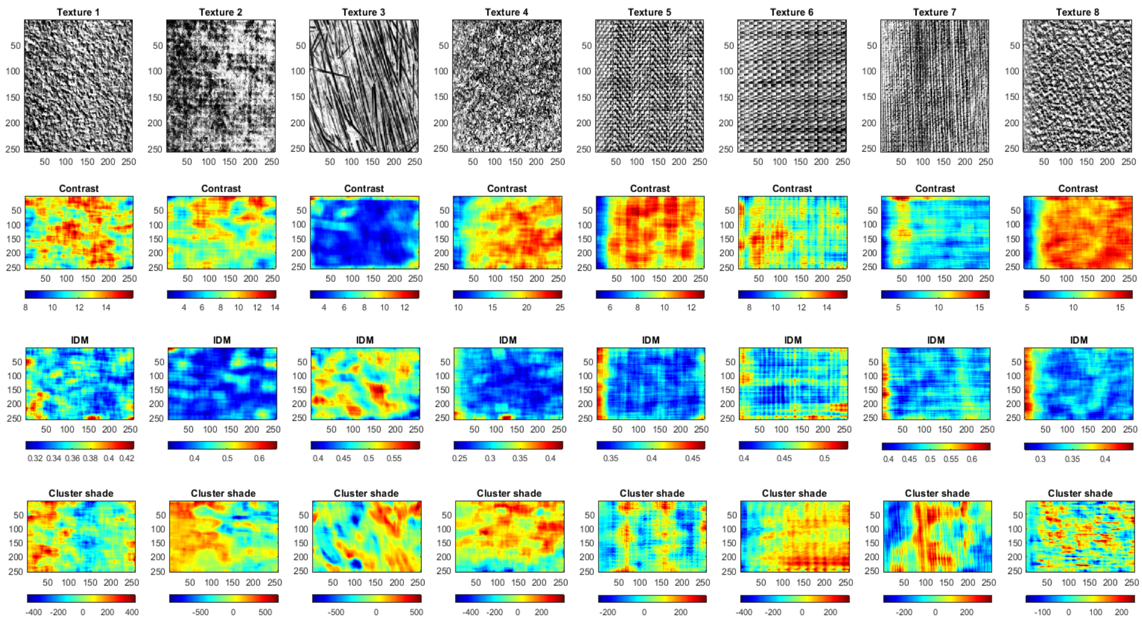


Figure 7: The histogram equalized textures and their corresponding GLCM features, consisting of contrast (or inertia), IDM and cluster shade. The GLCM features was computed using a sliding window of size 31. The GLCM features for texture 1, 2, 4 and 8 was computed using the isotropic GLCM matrix. The texture 3 GLCM features was computed by averaging $\theta \in \{0,135\}$. Texture 5 and 6 was computed by averaging $\theta \in \{0,90\}$ and texture 7 GLCM was computed using only $\theta \in \{0\}$.

In order to segment and separate the different textures in Mosaic 1 and Mosaic 2, as presented in Figure 1, various GLCM feature computation testing was performed, and by using various threshold values. The results from isotropic GLCM feature computations with global threshold, which gave the best segmentation results, are presented in Figure 8. For texture 2, texture 3, texture 4, texture 6 and texture 8 we found some suitable threshold values and GLCM features for segmentation. For texture 1 and texture 7 we could not find a suitable threshold in order to segment the textures using only one feature. However, by combining (multiplying) two features with different threshold we were able to segment out texture 1 and texture 7, with subpar results. The segmented texture 1 and texture 7 are presented in Figure 10. Texture 1 was segmented by combining contrast and IDM, and texture 7 was segmented by combining contrast and cluster shade.

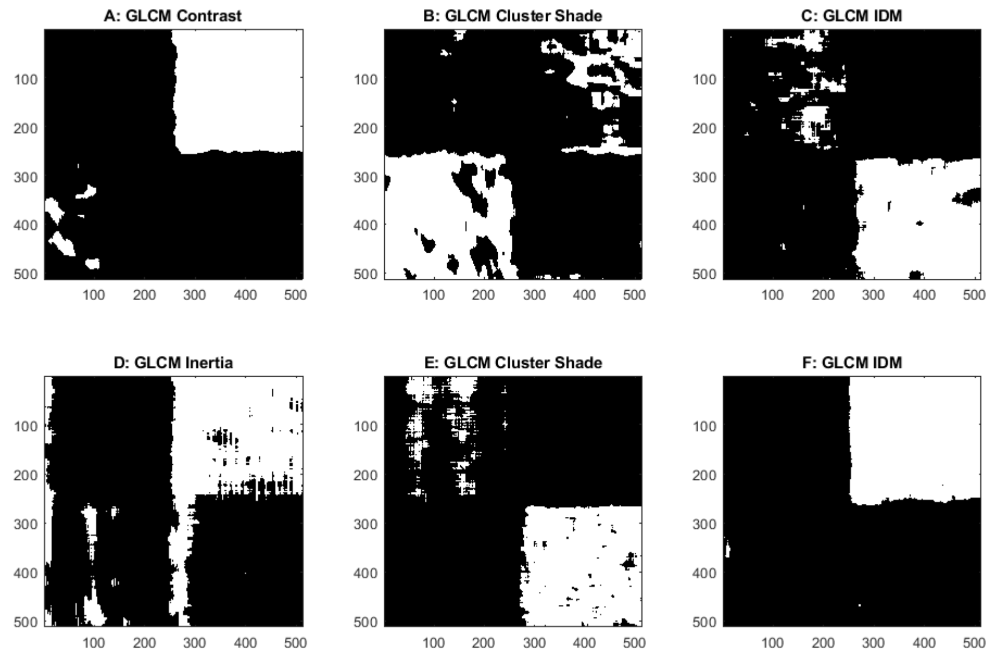


Figure 8: The threshold GLCM features computed on Mosaic 1 (A, B and C) and Mosaic 2 (D, E and F). The GLCM features was computed using isotropic GLCM matrix.

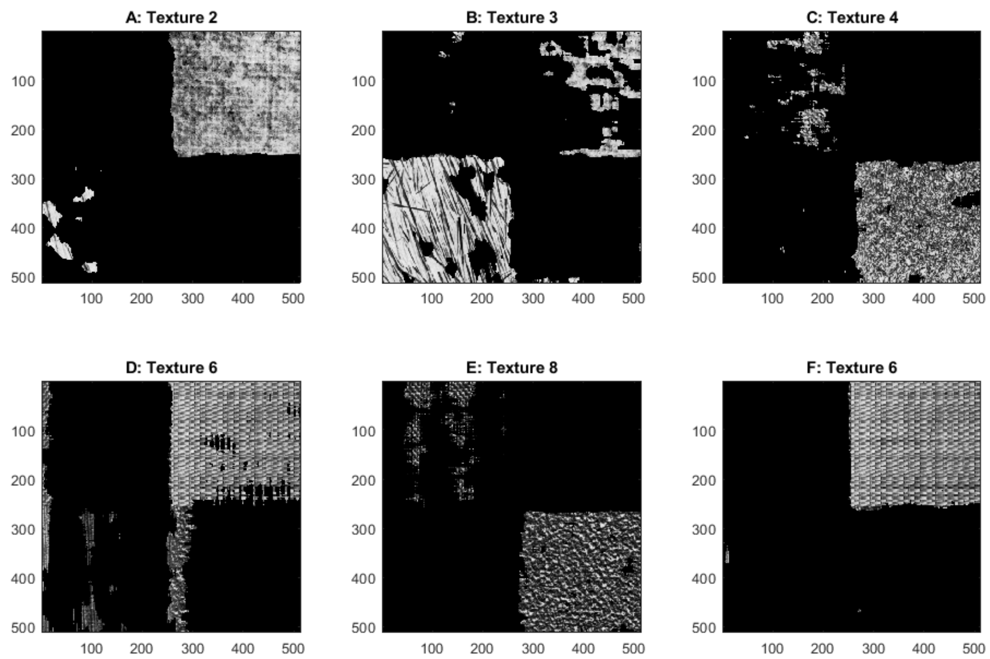


Figure 9: Segmented textures using the threshold GLCM features on Mosaic 1 (A, B and C) and Mosaic 2 (D, E and F), as presented in Figure 8. By using isotropic GLCM matrix for GLCM feature computations, we could not find a suitable threshold in order to segment texture 1 and texture 7. IDM feature for texture 6 (F) looks very promising.

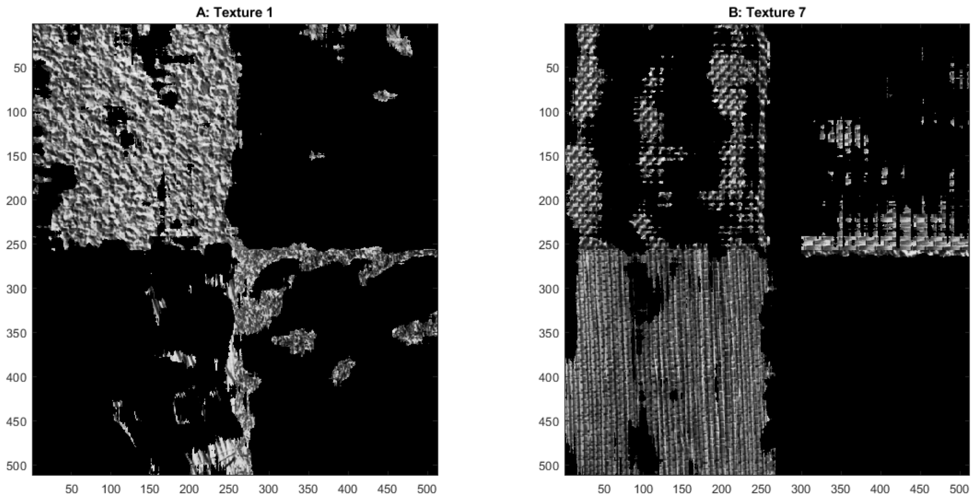


Figure 10: Segmented textures using the threshold GLCM features on Mosaic 1 (A) and Mosaic 2 (B). Texture 1 was segmented by combining contrast and IDM, and texture 7 was segmented by combining contrast and cluster shade.