Author(s): Saastamoinen, Kalle & Sari Penttinen

Title: Visual seabed classification using k-means clustering, CIELAB colors and Gabor-filters

Year: 2021

Version: Published version

Please cite the original version: Kalle Saastamoinen, Sari Penttinen,
Visual seabed classification using k-means clustering, CIELAB colors and Gabor-filters,
Procedia Computer Science,
Volume 192,
2021,
Pages 2471-2478,
ISSN 1877-0509,
https://doi.org/10.1016/j.procs.2021.09.016.

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 192 (2021) 2471–2478

Procedia Computer Science

www.elsevier.com/locate/procedia

25th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

Visual seabed classification using k-means clustering, CIELAB colors and Gabor-filters

Kalle Saastamoinen[a]*, Sari Penttinen[b]

[a]*Department of Military Technology, National Defence University, P.O. Box 7, FI-00861 Helsinki*
[b]*Naval Academy, P.O. Box 5, FI-20241 Turku*

Abstract

In this article, we discuss visual classification using unsupervised learning combined with methods that originate from human vision to divide the Baltic seabed to the soft and hard areas.

Seabed classification plays an important role in an understanding the undersea environment. Seabed can be characterized to be as muddy, rocky or sandy. Mine countermeasures (MCM) missions normally are clearance and/or route finding types and in both of these cases successful detection and classification is strongly connected of seabed type.

As our unsupervised learning method, we used k-means clustering. When we filtered our gray-scale seabed picture using Gabor filters, we noticed significant improvement after we segmented filtered image with k-means. We will also show results that we achieved using k-means alone and with Lab colors that are designed to approximate human vision.

Keywords: Visual analysis; clustering; k-means; Lab-colors; Gabor-filters

* Corresponding author. Tel.: +358407606489.
E-mail address: kalle.saastamoinen@mil.fi

1877-0509
10.1016/j.procs.2021.09.016

1. Introduction

Many activities related to seabed exploration as marine geology, ecology, oil industry, laying of pipelines and cables on the seafloor, designing and construction of hydrotechnical objects and navy operations need tools for fast and effective bottom recognition. [1] There are many studies of the identification of the sea bottom area [1,2,3,4,5,6,7,8,9]. In this study, we will concentrate on two techniques that are both inspired by human vision that are Gabor filters and Lab colors.

The aim of the seabed classification in the Finnish Navy is to be able to distinguish between hard and soft seabed of the Baltic Sea. Bottom of the Baltic Sea is multiform making it challenging to classify, diversified types of sediments, geomorphologic forms, and benthic habitats characterize it [1]. More detailed explanation of Baltic Seabed diversity one can check dissertation from 2017 by Anu Kaskela [10]. In practice, man is able visually to distinguish rock, sand, and mud from Side Scan Sonar (SSS) image. However, it is impossible to tell visually whether there is only a thin layer of mud or sand and something else beneath it. In Finnish coastal fleet year 2019, various classification and analysis methods have been reviewed and this article lists some of the experiments performed, their theory and methods used, as well as the future of this research.

Side Scan Sonar (SSS) is a sonar system, which is used to create an image of relatively large areas of the seafloor. It maps the seabed for a wide variety of purposes such as detection and identification of underwater objects and bathymetric features. SSS imagery is also a commonly used tool to detect debris and other obstructions on the seafloor. SSS creates an image of the seabed by transmitting a conical or fan-shaped sound signal, where echoes reflections successive lines form an image [11]. The signal level and the delayed additional echoes form distinct textures into the image created and carry information about the seabed properties. We see that use of image analysis technique is a natural choice and due to highly textured appearance of sonar images, texture analysis techniques are a common choice for analyzing seafloor acoustic images [12].

The content of the paper is organized as follows: In Section 2 background of k-means, Lab colors and Gabor filters are explained. In Section 3, Experimental results are given and in Section 4, we will state the concluding remarks and future of this research.

2. Short background of the used methods

Here we will present shortly background how we used k-means clustering, Lab colors and Gabor filters. These methods were selected due their presumed ability to give good visual representation of the results.

2.1. Using K-means clustering

Clustering methods are widely used to organize similar patterns, texts, audio, figures, graphs etc. into the separate groups. Broadly speaking, clustering is the problem of grouping a data set into several groups such that, under some definition of "similarity," similar items are in the same group and dissimilar items are in different groups [13].

K-means clustering is a popular method that is commonly used to automatic partitioning of data set into the k-groups [14,15]. We used Matlab k-means clustering that is also called Lloyd's algorithm [16]. The algorithm 1 [17] proceeds as follows:

1. Choose k initial cluster centers (centroid).
2. Compute point-to-cluster-centroid distances of all observations to each centroid.
3. Assign each observation to the cluster with the closest centroid.
4. Compute the average of the observations in each cluster to obtain k new centroid locations.
5. Repeat steps 2 through 4 until cluster assignments do not change filters.

2.2. Using CIELAB colors

The CIELAB color space here referred to simply as Lab, is a color space defined by the International Commission on Illumination (CIE) in 1976. It is designed to approximate human vision. Colour spaces usually either model the human vision system or describe device dependent colour appearances. Although there exist many different colour spaces for human vision, those standardized by the CIE (i.e. XYZ, CIE Lab and CIE Luv) have gained the greatest popularity. [18]

We used Matlab color-based segmentation with k-means clustering [19]. The algorithm 2 [20] proceeds as follows:

1. Read Image
2. Convert image from RGB color space to Lab color space
3. Classify the colors in 'ab' space using k-means clustering
4. Create images that segment the original image by color
5. Segment the nuclei filters.

2.3. Using Gabor filters

Gabor filter mainly provides means for better spatial localization. The main intention of employing Gabor filter is for texture segmentation. Filter Gabor is a Gaussian function that is multiplied by the harmonic function. Filters Gabor focus on a specific range of frequencies. If the input image contains two different texture areas, the local frequency difference between regions will detect the texture in one or more sub-image output filters. [20]

When we want to supplement the image with information about the texture in the neighborhood of each pixel, we filter a grayscale version of the image with a set of Gabor filters. [21]

The algorithm 3 [20] proceeds as follows:

1. Read Image
2. Segment the image into two regions using k-means clustering
3. Create a set of 24 Gabor filters, covering 6 wavelengths and 4 orientations
4. Convert the image to grayscale
5. Filter the grayscale image using the Gabor filters
6. Smooth each filtered image to remove local variations
7. Supplement the information about each pixel with spatial location information
8. Concatenate the intensity information, neighborhood texture information, and spatial information about each pixel
9. Segment the image into two regions using k-means clustering with the supplemented feature set

3. Segmentation of the seabed with results

In all our methods we used k-means clustering in order to do segment our image. Here we show example results by using original image called “rocky sea bottom”.

3.1. Segmentation using k-means

K-means clustering is unsupervised learning algorithm that produces k-areas of the image that are computationally closest to each other.

Original SSS-figure looks like Fig. 1.

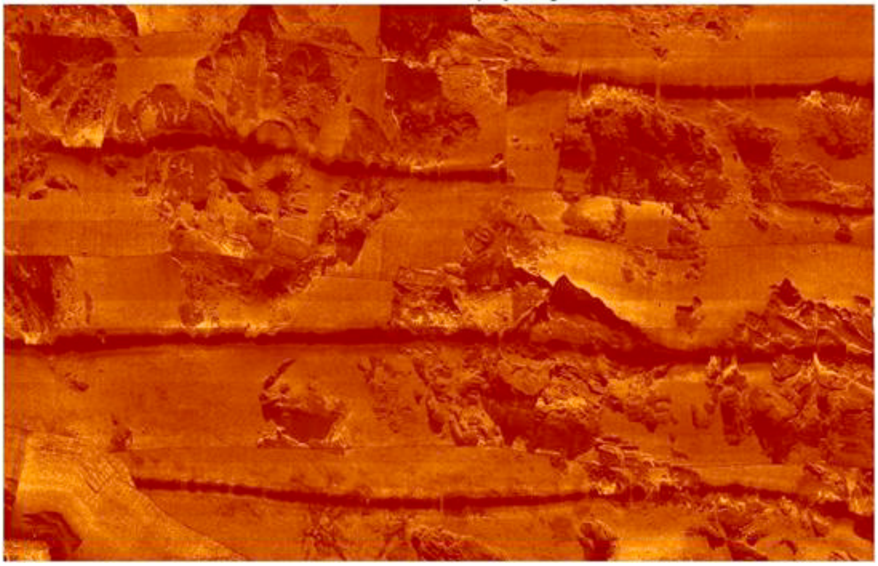

Fig. 1. Side-scan sonar picture 'rocky sea bottom'.

After we segment this into two areas using algorithm 1 we get following Fig. 2.

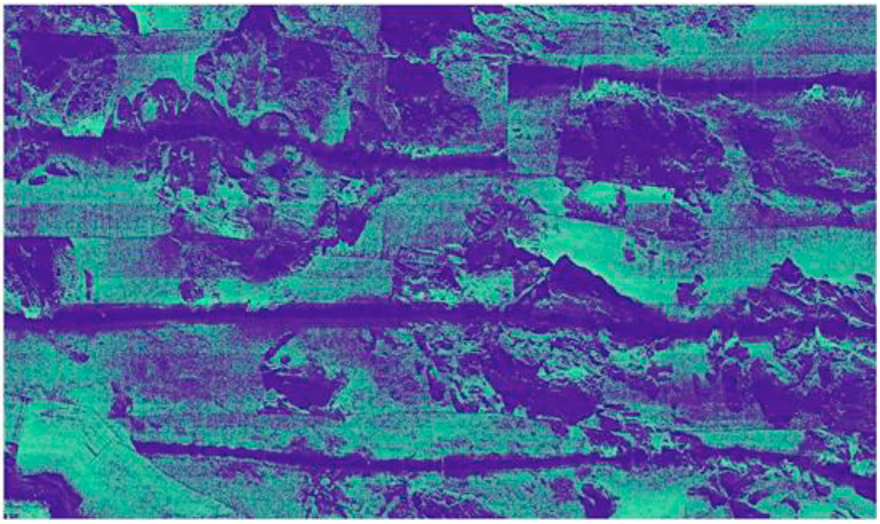

Fig. 2. Side-scan sonar picture 'rocky sea bottom' segmented to two areas using k-means clustering.

3.2. Segmentation using CIELAB colors

First we convert Image from RGB Color Space to Lab color space. Second we Classify the Colors in ab space using k-means clustering. Color information exists in the ab color space, our objects are pixels with a and b values. We use clustering to cluster our image into three clusters that have labeled every pixel in the image with its pixel label. [19] We reach the following Fig. 3 that is labeled by cluster index.

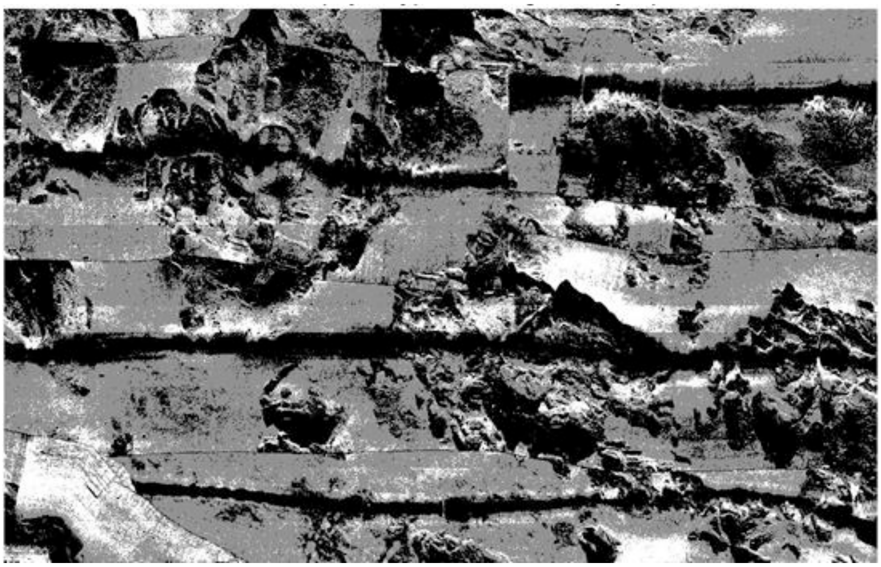

Fig. 3. Side-scan sonar picture ’rocky sea bottom sea’ labeled by cluster index.

Next we create images that segment Fig. 3 by color. [19] Using pixel labels we reach three images divided by colors Fig. 4.

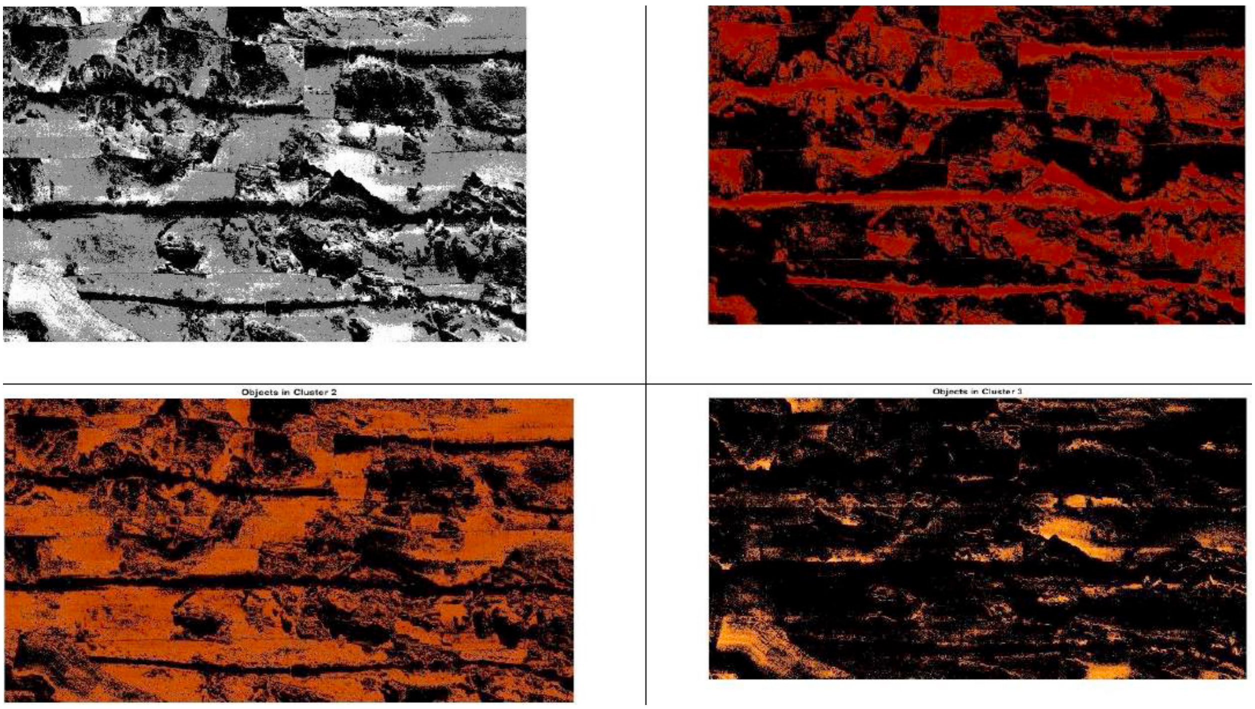

Fig. 4. Lab color-based clustering: ‘rocky sea bottom’ every pixel labeled up-left, Cluster 1 up-right, Cluster 2 down left, Cluster 3 down right. Here we can clearly see hard areas in up-right picture as being those red areas and soft parts as black. Down left hard parts are black.

Cluster 1 contains the red objects. There are dark and light red objects. We can separate dark red from light red using the L layer in the Lab color space. The cell nuclei are dark red. After this we reach Fig. 5.

Fig. 5. Only dark red cell nuclei are visible from Cluster 3. Red parts represent hard rock bottom.

3.3. Segmentation using Gabor-filters

Here we will improve the k-means segmentation presented in Fig. 2 by supplementing the information about each pixel and supplementing the image with information about the texture in the neighborhood of each pixel. To obtain the texture information we filter a grayscale version of the image Fig. 6 with a set of Gabor filters. We created a set of 24 Gabor filters, covering 6 wavelengths and 4 orientations. [21]

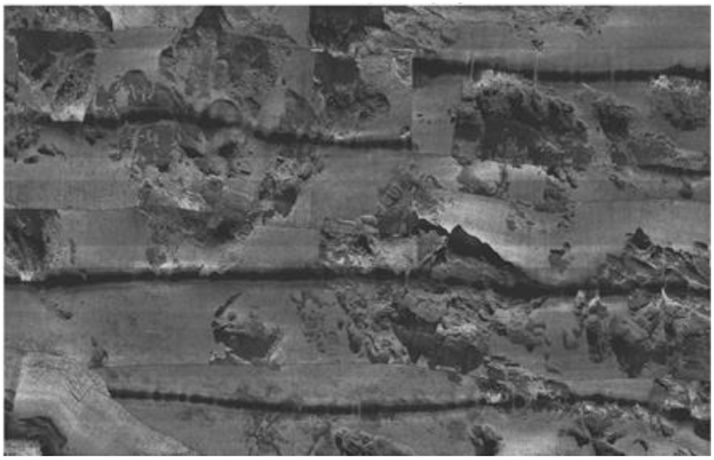

Fig. 6. Side scan sonar picture 'rocky sea bottom' in grayscale.

After we filtered and smoothed side-scan sonar picture 'rocky sea bottom' with our 24 Gabor filters we supplemented this information about each pixel with spatial location information. This additional information allows the k-means clustering algorithm to prefer groupings that are close together spatially. Next, we concatenate the intensity information, neighborhood texture information, and spatial information about each pixel. [21] After this, we segment the image into two regions using k-means clustering with the supplemented feature set as result we get the Fig. 7.

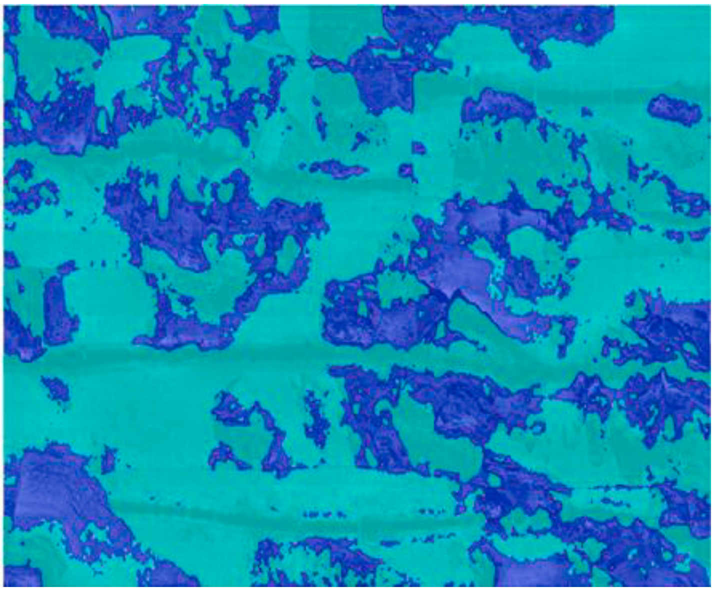

Fig. 7. Side scan sonar picture 'rocky sea bottom' segmented to two areas using k-means clustering with additional pixel information. Here dark green areas represent hard areas while light green and blue areas are soft mud and sand.

4. Conclusions and future

We managed to improve our visual view of segmentation results done by k-means clustering alone see Fig. 2 by using CIELAB color space see Fig. 5 and by using Gabor-filtering see Fig. 7.

Use of Lab colors was quite time consuming and included a lot of handwork, which is a major disadvantage of it. On the another hand Gabor-filters gave promising results with much less human involvement so wavelet approach is more promising for the future research, as we consider automated visual seabed type recognition. A major disadvantage of the Gabor filter is that the outputs of its filter banks are not mutually orthogonal, which may result in significant correlation between texture features [12].

In future we will improve texture analysis by tuning used wavelet base. It is known that energies of the wavelet coefficients are powerful features for discrimination of different seabed textures [12]. There are also different unsupervised learning algorithms that can be used and tuned to master Baltic seabed classification task.

Experiments presented in this research give grounds to believe that from the image obtained from the sonar, it is possible to distinguish features that tell whether the surface is hard or soft. Improved signal analysis can also in future tell how thick seabed layer is.

Acknowledgements

We are grateful to the Finnish Coastal Fleet and National Defence University, which gave us the opportunity to conduct this research.

References

[1] Tegowski, J., Nowak, J., Moskalik, M., & Szefler, K. (2011, June). Seabed classification from multibeam echosounder backscatter data using wavelet transformation and neural network approach. *In Proceedings of 4th International Conference and Exhibition on Underwater Acoustic Measurements: Technologies & Results*, 20th to 24th June (pp. 1257-1264).

[2] Javidan, R., & Eghbali, H. J. (2004, September). Designing and Improving a Receiver of an Active Sonar System Using Fuzzy Logic. In *5th Iranian Conference on Fuzzy Systems* (pp. 7-9).

[3] Williams, D. P. (2009). Bayesian data fusion of multiview synthetic aperture sonar imagery for seabed classification. *IEEE Transactions on Image Processing*, 18(6), 1239-1254.

[4] Petillot, Y., Reed, S., Coiras, E., & Bell, J. (2006). A framework for evaluating underwater mine detection and classification algorithms using augmented reality. *Proc. Undersea Defence Technology*.

[5] Van Komen, D., Neilsen, T. B., Knobles, D. P., & Badiey, M. (2019, May). A convolutional neural network for source range and ocean seabed classification using pressure time-series. In *Proceedings of Meetings on Acoustics* 177ASA (Vol. 36, No. 1, p. 070004). Acoustical Society of America.

[6] Preston, J. M., Christney, A. C., Bloomer, S. F., & Beaudet, I. L. (2001, November). Seabed classification of multibeam sonar images. In MTS/IEEE Oceans 2001. *An Ocean Odyssey. Conference Proceedings* (IEEE Cat. No. 01CH37295) (Vol. 4, pp. 2616-2623). IEEE.

[7] Preston, J. M., Christney, A. C., Beran, L. S., & Collins, W. T. (2004, July). Statistical seabed segmentation—from images and echoes to objective clustering. In *Proceedings of the Seventh European Conference on Underwater Acoustics*, ECUA (pp. 5-8).

[8] Pican, N., Trucco, E., Ross, M., Lane, D. M., Petillot, Y., & Ruiz, I. T. (1998, September). Texture analysis for seabed classification: co-occurrence matrices vs. self-organizing maps. In *IEEE Oceanic Engineering Society. OCEANS'98. Conference Proceedings* (Cat. No. 98CH36259) (Vol. 1, pp. 424-428). IEEE.

[9] Williams, D. P. (2009, November). Unsupervised seabed segmentation of synthetic aperture sonar imagery via wavelet features and spectral clustering. In *2009 16th IEEE International Conference on Image Processing (ICIP)* (pp. 557-560). IEEE.

[10] Kaskela, A. (2017). *Seabed landscapes of the Baltic Sea Geological characterization of the seabed environment with spatial analysis techniques*. Available: https://tupa.gtk.fi/julkaisu/erikoisjulkaisu/ej_100.pdf (Retrieved 2.6.2021)

[11] Finkl, C. W., & Makowski, C. (Eds.). (2016*). Seafloor Mapping Along Continental Shelves: Research and Techniques for Visualizing Benthic Environments* (Vol. 13). Springer.

[12] Javidan, R., & Eghbali, H. J. (2007). Automatic seabed texture segmentation and classification based on wavelet transform and fuzzy approach. *Underwater Technology*, 27(2), 57-65.

[13] Guha, S., & Mishra, N. (2016). Clustering data streams. In *Data stream management* (pp. 169-187). Springer, Berlin, Heidelberg.

[14] MacQueen, J. (1967, June). Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability* (Vol. 1, No. 14, pp. 281-297).

[15] Wagstaff, K., Cardie, C., Rogers, S., & Schrödl, S. (2001, June). Constrained k-means clustering with background knowledge. In *Icml* (Vol. 1, pp. 577-584).

[16] Lloyd, S. (1982). Least squares quantization in PCM. *IEEE transactions on information theory*, 28(2), 129-137.

[17] Matlab. 2020. Retrieved April 23, 2020 from https://se.mathworks.com/help/stats/kmeans.html

[18] Baldevbhai, P. J., & Anand, R. S. (2012). Color image segmentation for medical images using L* a* b* color space. *IOSR Journal of Electronics and Communication Engineering*, 1(2), 24-45.

[19] Matlab. 2020. Retrieved April 23, 2020 from https://se.mathworks.com/help/images/color-based-segmentation-using-k-means-clustering.html

[20] Premana, A., Wijaya, A. P., & Soeleman, M. A. (2017, October). Image segmentation using Gabor filter and K-means clustering method. In *2017 International Seminar on Application for Technology of Information and Communication (iSemantic)* (pp. 95-99). IEEE.

[21] Matlab. 2020. Retrieved April 23, 2020 from https://se.mathworks.com/help/images/ref/imsegkmeans.html