K-means Clustering based on Multiresolution images and Spatial Constraints

M.Yaghmorasan Benzian
Computer Science Department
University Abou Bekr Belkaid of Tlemcen
Tlemcen, Algeria
mohammed.benzian@univ-usto.dz

N.Benamrane
Computer Science Department
University of Science and Technology Oran USTO-MB, Algeria
Oran, Algeria
nacera.benamrane@univ-usto.dz

Abstract—This paper proposes a new K-means segmentation approach applied on multiresolution images and based on spatial constraints. K-means clustering is performed first on various image resolution levels where the limit of resolution level can reach 1/8th of image. Then, clustering result of each pixel p of the original image can be updated depending on clustering result k on lower resolution images and on presence ratio of k in the spatial neighbourhood of p in the original image. Image analysis at lower resolution allows having rough clustering result which means that a pixel is affected to a cluster to which the majority of its pixel neighbourhood belongs. The aim of this approach is to minimize clustering errors depending on the spatial cluster repartition at the neighbourhood of each pixel in order to get more homogeneous regions and eliminate noisy regions in the image. The approach is tested on simple and medical images by adding a gaussian noise and varying resolution level for a better analysis. The results of multiresolution clustering are satisfactory and a comparison is made with standard K-means.

Keywords—Segmentation, K-means, Multiresolution, Gaussian Noise, Spatial Constraints, Clustering

I. Introduction

Image segmentation is one of the most important fields in computer vision because of its crucial impact in image processing systems. K-means method is widely used in image classification and segmentation, because of its implementation simplicity and rapidity. Many image segmentation approaches using K-means method have been proposed. Some approaches integrated multiresolution analysis, others combined diverse factors such as spatial or neighborhood constraints, region growing or genetic algorithms.

Tamir et al. [11] proposed a K-means mulitresolution clustering method that applies K-means algorithm to a sequence of resolution levels that monotonically increases at each clustering stage. Zhang et al. [12] proposed a technique that integrates neighborhood constraints into the standard k-means algorithm for segmenting high-resolution spatial hyperspectral images. The utilization of neighborhood window enables to optimize class centers by reducing noise interference and heterogeneity caused by spectral and spatial variation in high-resolution images. Luo et al. [7] proposed a K-means segmentation approach that incorporates spatial constraints. The method is executed in two phases: in the first one a hierarchical iteration of region growing with spatial constraints is processed. The second phase concerns merging process, which merges over-segmented regions and refines the boundaries of regions. Guan et al. [3] proposed a hybrid image segmentation method that combines k-means and density-based spatial clustering of applications with noise.

Li and Chiao [6] proposed a texture segmentation approach that combines K-means method and genetic algorithm within a multiresolution structure that propagates the results from the coarsest level to the finest level. A dynamic and incremental K-means clustering approach was proposed by Aaron et al. [1], which allows, initially from a large number of clusters, to dynamically decrease the number of clusters in each phase until a final reduced number is reached. Ilea and Whelan [5] also proposed an approach of color image segmentation using spatial K-means algorithm. Applied spatial constraints solve the problem of texture complexity by identifying continuous clusters in color images. Chandhok et al. [2] also proposed a K-means color image segmentation approach by integrating spatial characteristics, followed by a merging process of segmented areas into a specific number of regions. Ngah et al. [10] proposed an automated segmentation approach that combines region growing and moving K-means clustering for the detection of abnormalities in a region of interest in mammographic microcalcifications.

In section 2, we give a description of the standard K-means clustering method which is based on an iterative process. In Section 3, we present the new K-means segmentation approach based on multiresolution image analysis while integrating the spatial constraints in the neighborhood of each pixel cluster. Experimental results on simple and medical images with the presence of Gaussian noise are then shown in Section 4 by varying the resolution level limit of each image. In this section, a comparison is made with the standard K-means method followed by a discussion. Finally, in section 5 a conclusion is presented with general perspectives for the new approach.

II. K-Means Clustering

K-Means is a non-hierarchical clustering technique that aims to distribute a population of data into K classes (or partitions) in which each data item D belongs to a class K such as the measure of distance or similarity between data D and cluster center K are the closest possible [9]. K-means is performed iteratively so that an object associated with a class during one iteration can be assigned to another class at the next iteration, because cluster centroids are redefined at each iteration step [4, 8].

In the first iteration, the centres of k classes are assigned to k objects selected randomly or according to a defined criterion. Then, the distance between objects and k centres is calculated, and objects are assigned to the centroids to which they are closest. Cluster centroids are then redefined from the objects that have been assigned to the different classes, and the objects are then reassigned according to their distance to the new centroids. The process is repeated iteratively until a convergence criterion is reached.

K-means algorithm is executed as follows:

1. Initialization, by defining the number of clusters and selecting randomly the cluster centroids.

2. Generate a new partition by assigning each object to the nearest cluster centroid (i.e perform a voronoi partition based on

averages).

$$S_i^{(t)} = \left\{x_{j:} \left\| x_j - m_i^{(t)} \right\| \le \left\| x_j - m_{i^*}^{(t)} \right\| \forall i^* = 1,\dots,k \right\} \quad (1)$$

3. Update the average of each cluster

4. Repeat steps 2 and 3 until the convergence criterion is reached, i.e. objects become stable and do not change their cluster membership.

This method therefore aims to maximize the similarity within each class of an objective function:

$$J = \sum_{i=1}^{K} \sum_{x_j \in C_i} d(x_j, C_i) \quad (2)$$

In the case of Euclidean distance, J is considered a quadratic error function.

$$J = \sum_{i=1}^{K} \sum_{x_j \in C_i} \left\| x_j - C_i \right\|^2 \quad (3)$$

III. PROPOSED APPROACH

A. *K-means multiresolution segmentation presentation*

In our approach we used several image resolution levels and the maximal limit of resolution level was fixed to three. In section 4 of experimental results, several tests have been carried out where the limit of the resolution level can be fixed to 1, 2 or 3.

The principle of computing low resolution images was done with the Bartlett filter. The Bartlett Smoothing Filter mask (3 x 3) computes a low-scale image whose height and width are halved. To compute an image at a more lower resolution level (2nd or 3rd level), a composition of the Bartlett filter (eq.4) is applied 2 (respectively 3) times successively.

$$h_{bartlett}^{3\ x\ 3} \overset{def}{=} \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \quad (4)$$

First, K-means classical method is executed independently on different image resolution levels. Each image at low-scale has a grid or matrix of pixel values corresponding to the cluster indices to which each pixel has been assigned. For example, the scale image 1/2 contains a matrix of class values of size m / 2 lines by n / 2 columns, The scale image 1/4 (resp. 1/8) contains a matrix of m / 4 (resp., M / 8) lines per n / 4 (resp. n / 8) columns.

B. *Computation of Cluster Results by Pyramidal Propagation*

To obtain a cluster matrix of size corresponding to the original image (m lines by n columns) from each low-scale image, a calculation is made by pyramidal propagation from the smaller size corresponding to the image at lower scale up to the size of the original image (fig. 1). For each pixel in a higher resolution level, its cluster is computed from the prior low-resolution result according to the average of the clusters of its neighborhood, by convolving with the coefficients of Bartlett filter mask. The principle of calculating clusters between two successive resolution levels and corresponding to the implemented function Calc_KmeansScale is therefore as follows:

Given (x, y) the pixel position P in the low-scale image and the membership matrix to a certain cluster, the calculation of the cluster of P corresponding to the high-scale image in its new position (x * 2, y * 2) is as follows:

$$Kmeans\_Hres(x*2, y*2) = \frac{\sum_{i=-1}^{1} \sum_{j=-1}^{1} Kmeans(x+i, y+j) Bartlett(i+1, j+1)}{16} \quad (5)$$

Then, we assign to the horizontal and vertical odd positions of the high-resolution image the class to which the majority of the classes of its 3 direct neighbours previously computed (the 4th direct neighbour is not yet calculated by traversing increasingly the lines and columns), as:

$$KmeansHres(2x+1, 2y) = major\ clust\begin{pmatrix} KmeansHres(2.x, 2.y) \\ KmeansHres(2.x+1, 2.y-1) \\ KmeansHres(2.x+2, 2.y) \end{pmatrix} \quad (6)$$

The same principle is done for odd vertical position, and for both odd horizontal and vertical positions:

$$KmeansHres(2x, 2y+1) = major\ clust\begin{pmatrix} KmeansHres(2.x, 2.y) \\ KmeansHres(2.x-1, 2.y+1) \\ KmeansHres(2.x, 2.y+2) \end{pmatrix} \quad (7)$$

$$KmeansHres(2x+1, 2y+1) = major\ clust\begin{pmatrix} KmeansHres(2.x+i, 2.y+j), \\ -1 \le i \le 1, -1 \le j \le 1, i \ne j \end{pmatrix} \quad (8)$$

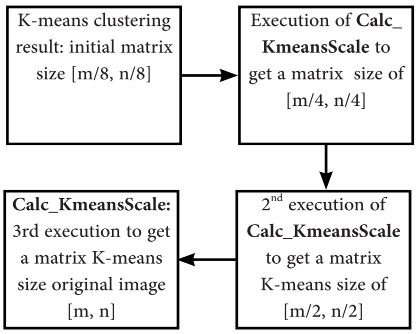


Fig.1. Pyramid propagation process from the lowest resolution image to the highest resolution, i.e. the original image

C. *Use of spatial constraints and cluster results in low resolution images*

After transofmring clustering results in the form of matrices of the same size as the original image, we now proceed to the last step by changing the membership cluster of the pixel P in the original image, according to the membership cluster value of the corresponding pixel in low-resolution images, and taking into consideration the spatial constraint criterion which necessitates that the presence rate of the new candidate cluster in the vicinity of P (on a window (3 x 3) or (5 x 5)) in the original image is greater than or equal to a certain threshold t.

Thus, among the clusters obtained on low-resolution images (1/2, 1/4 and 1/8) which are different from the cluster k_orig of the original image, the one which owns the largest ratio in the neighbourhood of P in the cluster of the original image will be assigned to this pixel P instead of k_orig.

The different image resolution levels are numbered successively from number (1) for the original image, to number (4) for the lowest resolution level image 1/8 or 12.5 %.

D. Algorithm of our approach

The general algorithm of our approach is summarized as follows:

1) _scale = _scale_limit (lowest level)

2) Application of the K-means method on different image resolution levels separately

3) For i = 2 to _scale_limit

4) Pyramidal transformation of the cluster matrix K from resolution level i to the one of the original image

4a) For j = i-1 downto 1 do

4b) Matrix_class (resol_level_j) = Calc_KmeansScale (Matrix_class (lower_resol_level j + 1))

4c) End For

5) End For

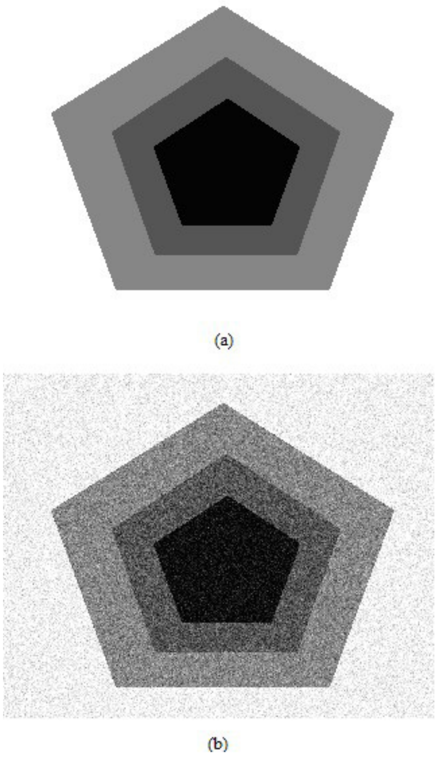
6) Modification of pixel clusters in the original image depending on cluster results obtained from low resolution images and spatial constraints.

IV. Experimental Results

The tests of our new approach were performed on a set of simple and medical images by adding gaussian noise to the images. To test the performance of our approach, the parameter _scale_limit corresponding to the limit of the resolution level -presented in section 3- was varied (taking values of 2, 3 or 4) because the segmentation result depends on this parameter. For spatial constraints, the neighbourhood window was set to a size of (3 x 3), and the threshold t was fixed to 30 % (0.3). A comparison is made between our approach and the standard K-means approach whose algorithm is described in [8].

The first test was applied on a simple noisy image constituted of four imbricated polygons with 5 sides and different colors (Figure 2). The number of clusters was set to 4. The clustering result with standard K-means (Fig. 2c) shows a high error rate compared to the result with multiresolution K-means which presents very lower error. The resolution level chosen is 3.

In the second trial, we used a CT liver image with a tumor lesion (Figure 3) with gaussian noise. The resolution level chosen was the 3rd one. Figure 3c shows clustering result with standard K-means and Figure 3d shows clustering result with multiresolution K-means which is significantly the better (Fig. 3c) with a much lower clustering error rate than standard K-means.



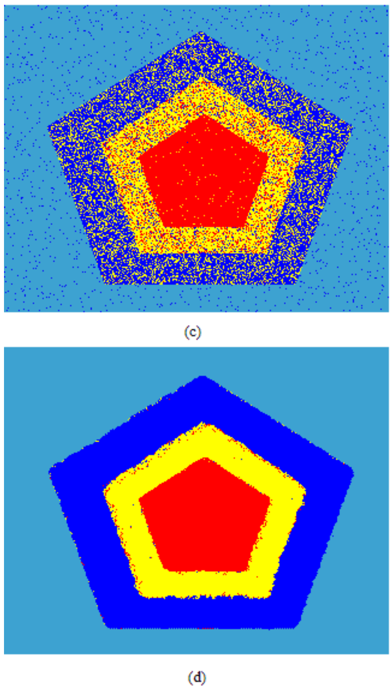
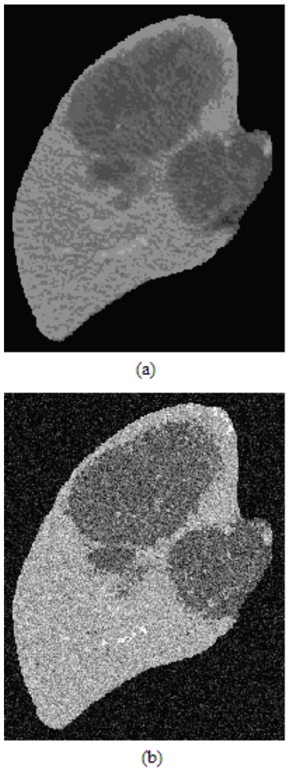
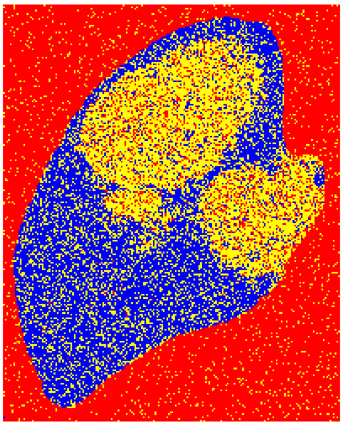
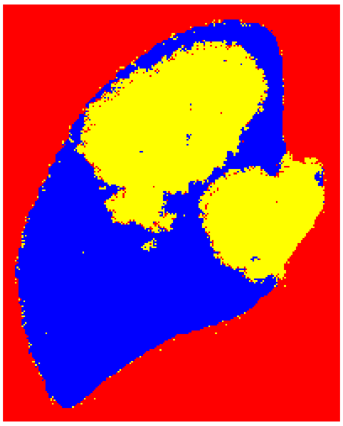


Fig.2. Simple image with gaussian noise. Original image (a), with added gaussian noise (b), result with standard K-means (c), and segmentation result with multiresolution K-means (d).





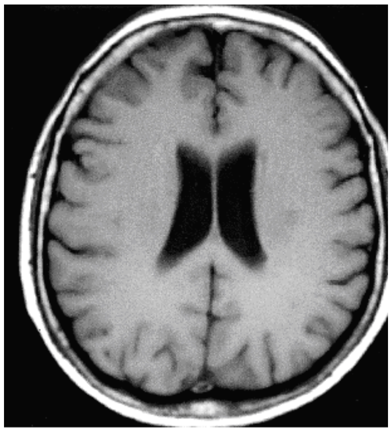
(c)



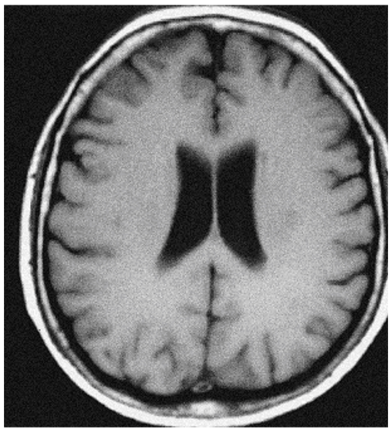
(d)

Fig.3. CT liver image with a tumoral zone. Original image (a), image with added gaussian noise (b), clustering result with standard K-means (c), and with multiresolution K-means (d)

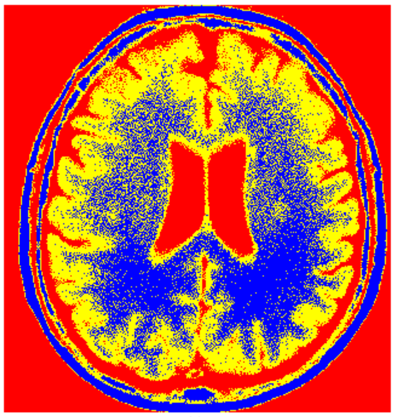
In Figure 4 a brain image is presented with 3 fixed classes: gray matter, white matter and cerebrospinal fluid. Gaussian noise was also added to the image, and the resolution level chosen is the 3rd. The clustering result with multiresolution K-means (Fig. 4d) is better than classical K-means (Fig. 4c). In Figure 5 a brain image with a meningitis area is shown. Three clusters were chosen, and the resolution level that has the best result for multiresolution K-means is the 2nd one. The clustering result with K-means (Fig. 5d) is better than classical K-means.



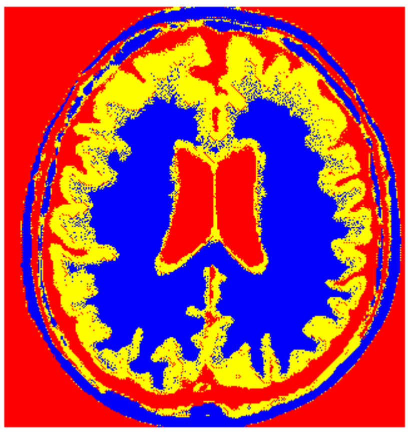
(a)



(b)



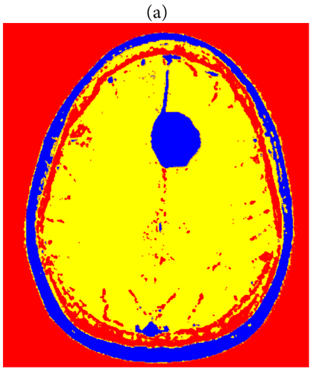
(c)



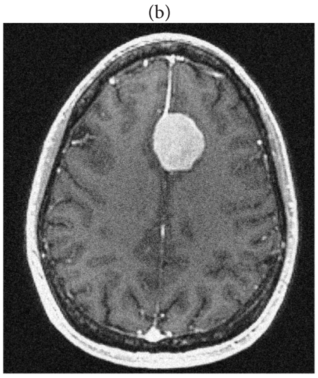
(d)

Fig.4. Brain image. Original image (a), image with gaussian noise (b), standard k-means result (c), and multiresolution K-means(d).

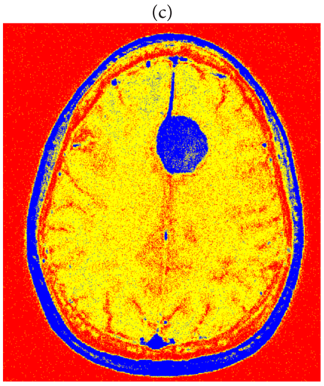
(a)



(b)



(c)



(d)

Fig.5. Brain image with meningitis. Original image (a), image with gaussian noise (b), clustering result with classical K-means (c), and with multiresolution K-means (d).

The experimental results were presented with a comparison between our approach and the standard K-means. However, the validation of these results remains insufficient. For this reason, another comparison is made with a reference manual segmentation by a medical expert applied to the images without gaussian noise.

The performance evaluation of the method is done by estimating wrong classified pixels in the entire image. The classification error rates given in Tables 1 and 2 are presented taking into account the Gaussian noise added in the image (for example: table 1 gives the classification error rates with the classical K-means and our multiresolution K-means approaches, the value chosen for multiresolution K-means corresponds to the minimum error rate given in table 2 which shows classification error rates by varying the limit of resolution level (_scale_limit = 1 corresponds to image resolution level 1/2 or 50%, _scale_limit = 2 (resp. 3) corresponds to resolution level 1/4 or 25% (resp. 1/8)).

We can affirm that the misclassification rate was significantly reduced with our multiresolution K-means approach compared with standrd K-means. And whatever the limit of resolution level, clustering error rate is always lower than that of the standard K-means.

TABLE I. RESULT VALIDATION WITH MANUAL SEGMENTATION AND COMPARISON WITH CLASSICAL AND MULTIRESOLUTION K-MEANS

Image type	**Total number of pixels**	**Number of clusters**	**Standard K-means error ratio**	**Multi-resolutionK-means error ratio**
Simple image	81920	4	12.92 %	2.02 %
CT liver	49600	3	19.92 %	6.38 %
Brain img 1	107520	3	22.33 %	15.84 %
Meningitis	460800	3	12.56 %	4.09 %

TABLE II. CLUSTERING ERROR RATIO WITH MULTIRESOLUTION K-MEANS BY VARYING THE PARAMETER LIMIT OF RESOLUTION LEVEL

Type d'image	**Kmeans multires resolut_ level _1**	**Kmeans multires resolut_lev _2**	**Kmeans multires resolut_ lev_3**
Simple image	2.02	2.37	4.14 %
CT liver	6.38 %	6.77 %	9.42 %
Brain img 1	16.23 %	15.84 %	19.34 %
Méningite	4.59 %	4.09 %	5.70 %

V. CONCLUSION

In this paper, we presented a new image segmentation approach using K-means multiresolution clustering and integrating spatial constraints. Clustering at several resolution levels permits to reduce false classifications in the images and thus eliminates the noise present in the image. The limit of the resolution level was fixed to the 3rd level which is the 1/8th of the image.

Our approach has been tested on simple images as well as medical images with Gaussian noise added in the original images. We used several values of the parameter _scale_limit corresponding to the limit of resolution level. Multiresolution clustering results are satisfactory and the misclassification rate in noisy images has been considerably reduced or eliminated with our approach, contrary to the classical K-means approach. Our approach would be further tested on other image types such as satellite or geographic images, as well as moving video images or 3D images.

References

[1] B. Aaron, D.E. Tamir, N. Rishe, and A. Kandel, “Dynamic incremental K-means clustering,” In: The 2014 International Conference on Computational Science and Computational Intelligence, Las Vegas, USA (2014)

[2] C. Chandhok, S. Chaturvedi, and A.A. Khurshid, “An Approach to Image Segmentation using Kmeans Clustering Algorithm,” Intern. Jrnl of Information Technology (IJIT) 1(1), (2012)

[3] Chun Guan, Kevin Kam Fung Yuen, and Qi Chen, “Towards a hybrid approach of k-means and density-based spatial clustering of applications with noise for image segmentation,” In Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), 2017 IEEE International Conference on, pp 396–399. IEEE, (2017).

[4] J.A. Hartigan and M.A. Wong, “Algorithm AS 136: A K-Means Clustering Algorithm, Journal of the Royal Statistical Society,” Series C, vol. 28, no 1, (1979)

[5] D.E. Ilea and P.F. Whelan, “Color image segmentation using a spatial k-means clustering algorithm,” in Proceedings of the Irish Machine Vision & Image Processing Conference, pp. 146–53, Dublin City University (2006)

[6] C. Li and R. Chia, “Multiresolution genetic clustering algorithm for texture segmentation,” Image and Vision Computing 21, 955–966 (2003)

[7] M. Luo, Y.F. Ma, and H.J. Zhang, “A Special Constrained K-Means approach to Image Segmentation”, proc. The 2003 Joint Conference of Fourth International Conference on Informations Communications and Signal Processing and the Fourth Pacific Rim Conference on Multimedia,vol.2, pp.738-742 (2003)

[8] S.P. Lloyd, “Least squares quantization in PCM,” IEEE Transactions on Information Theory 28 (2), pp 129–137 (1982)

[9] J.B. MacQueen, “Some methods for classification and analysis of multivariate observations,” Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability, vol. 1, pp. 281-297, (1967)

[10] U.K. Ngah, M. Isa and M.M. Noor, “Automated seed-based region growing using the moving K-means clustering for the detection of mammographic microcalcifications,” In Proc. of the World congress on Medical Physics and Biomedical Engineering, paper154, WC03 (2003)

[11] D.E. Tamir, C-Y. Park and W-S. Yoo, “The validity of pyramid K-means clustering,” Proc. SPIE conference on Optics and Photonics / Optical Engineering and Applications, pp 1225-1233, Sept (2007)

[12] B. Zhang, S. Li, C. Wu, L. Gao, W. Zhang and M. Peng, “Neighbourhood-constrained Kmeans Approach to Classify Very High Spatial Resolution Hyperspectral Imagery,” Remote Sensing Letters, 4: 161-170, (2013)