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COMPARATIVE ANALYSIS BETWEEN K-MEANS, FCM, AND CKMEANS ALGORITHMS FOR IMAGE SEGMENTATION

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ABSTRACT

Clustering algorithms are often used for image segmentation, aiming to group pixels by their similarity and uniformity. This process is useful to detect and highlight important areas of an image, making its analysis easier in several applications such as remote sensing and medical diagnosis. This paper have the main objective to compare the K-Means hard clustering algorithm to the FCM and ckMeans fuzzy clustering algorithms in image segmentation applications, using the R statistical programming language for analysis and visualization of the results. Uncertainty in the clustering process is discussed via the use of the alpha-cut parameter. Two experiments were conducted, using an image from an open database and an aerial image of a *Catarinense* city. It was found that the three methods produced similar results, when crisp clusters were considered. Fuzzy membership results of FCM and ckMeans were also compared, and it was found that, although very similar, ckMeans produced slightly lower levels of uncertainty than FCM. It was found that K-Means presents the best computational performance among the algorithms compared, which is expected due to its crisp nature. Among the fuzzy algorithms compared, ckMeans presented better performance, and FCM required less memory.

Keywords: Image processing. Statistical programming. Remote sensing**.**

1 Introduction

Image segmentation is an important step in image processing and it is useful for analyzing the components of an image. Image segmentation is the process of partitioning a digital image into multiple distinct regions, containing clusters of pixels (sets of pixels, also known as super pixels) with similar attributes. Clustering algorithm's objective to organize a set of objects into clusters such that items within a given cluster have a high degree of similarity, while items belonging to different clusters have a high degree of dissimilarity [1].

In addition, the use of clustering techniques in the process of image segmentation allows to group similar data, describing singular characteristics of each one of the identified groups. This process allows the development of classification schemes for finding interesting relationships between attributes of the data that would not be easily visualized without using such techniques.

Popular clustering algorithms used in image segmentation are K-Means [2], for hard classification, and Fuzzy C-Means (FCM) [3], for soft classification. Those algorithms can be found in readily available toolboxes, such as the fuzzy

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clustering package developed by [4] using the R statistical programming language. Less popular than those, there is the ckMeans algorithm developed by [5], which can be considered a hybrid of K-Means and FCM.

While there are many studies applying those clustering algorithms to tabular data, there are fewer examples of their application to raster images. Furthermore, the uncertainties inherent to the clustering process are seldom explored in the literature [6] used an α-cut parameter to highlight pixels with membership degrees below a certain threshold, and this paper aims to expand that study by comparing the results of the K-Means, ckMeans and FCM algorithms, to further explore their results in image segmentation problems.

In this sense, this paper has the main objective to compare the K-Means hard clustering algorithm to the FCM and ckMeans fuzzy clustering algorithms in image segmentation applications, using the R statistical programming language for analysis and visualization of the results.

2 Material and methods

2.1 ckMeans Algorithm

The ckMeans clustering algorithm, developed by [8], is based on the FCM [9][3] and K-Means [2] clustering algorithms, with some similarities and differences which are detailed in this section. The main objective of clustering algorithms is to partition a finite collection of n elements $X = x_1, x_2, \dots, x_n$ into p clusters. In fuzzy clustering, the cluster j to which each item x_i belongs to is expressed by a membership degree M_{ij} on a matrix M.

The ckMeans algorithm [5] receives as input a matrix containing the n data points, the number of clusters p and the value of the fuzzification parameter m in the range $(1; w)$, indicating the width of the n-dimensional cluster perimeter. We only consider rational values of m to simplify the calculation of Equations (3), and (2). According to [10], m is usually in the range (1,25; 2).

The algorithm is executed in 6 steps:

1 - The M (membership degree matrix) is initialised with a random value between zero and 1. The sum of pertinence degrees of each data point must be 1.

2 - A new membership matrix, called MCrisp, is created by one-hot encoding the fuzzy membership matrix M. This process is done by assigning 1 to the position of the highest membership cluster in each line of M, and 0 to the others. Each element of the MCrisp matrix is referred to as $M\text{Crisp}_{ij}$, where ij is the element's position.

3 - After the MCrisp matrix is calculated, the new cluster centroids c_j are calculated by adding the data belonging to the cluster (in crisp form) and dividing the result by the number of objects classified in that cluster, as per Equation (1).

$$c_j = \frac{\Sigma_{i=1}^{n} x_i MCrisp_{ij}}{\Sigma_{i=1}^{n} MCrisp_{ij}} \qquad (1)$$

4 - Calculate the table of the fuzzy membership function as shown in Equation (2).

$$M_{ij} = \frac{\left(\frac{1}{d_{ij}(x_i;c_j)}\right)^{\frac{2}{m-1}}}{\sum_{k=1}^{p}\left(\frac{1}{d_{ik}(x_i;c_k)}\right)^{\frac{2}{m-1}}} \qquad (2)$$

5 - Calculate the value of the objective function shown in Equation (3).

$$J = \sum_{i=1}^{n}\sum_{j=1}^{p} M_{ij}^{m}\, d_{ij}\left(x_i; c_j\right)^2 \qquad (3)$$

Where:

- n; is the number of data points;
- p: is the number of output clusters;
- x_i: is a vector of training data, Where (i= 1, 2,...n). These are the cluster attributes selected from the source data elements (such as columns in a database table or RGB values of the pixels in an image).
-c_j: the centroid (or center) of a fuzzy cluster (j= 1,2,....,p);
- $d_{ij}(xi;c_j)$: is the Euclidian distance between x_i and c_j.

The value of this objective function is used in step 6, as a stop condition.

6 - Return to step 2 until a convergence condition is reached. This can be when a fixed number of iterations is reached, or when the value of the objective function (Equation 3) converges to a user-input convergence parameter $\varepsilon > 0$, as per Equation 4.

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$$d_{ij}(J_U;J_A) \leq \epsilon \qquad (4)$$

Where:
- J_a: is the value of the objective function calculated in the previous iteration;
- J_u: is the objective function calculated in the current iteration.

2.2 Alpha-cut

A fuzzy set is a collection of objects with various degrees of membership to a set of given groups. Often, it is useful to consider for analysis those elements that have at least some minimal membership degrees a. This is akin to asking who has a passing grade in a class, or a minimum height to ride on a roller coaster [11][12]. We call this process an α–cut. It is important to note that the result of applying α-cut to a fuzzy set is a crisp set. The α-cut parameter is an addition to the original versions of ckMeans and FCM.

For every α in the range (0;1), a given fuzzy set A yields a crisp set Aa which contains those elements of the universe X who have membership degree in A of at least a (Equation 5).

$$A^{\alpha} = \{x \in X | A(x) \geq \alpha\} \qquad (5)$$

2.3 Implementation

The analyses presented in this paper were carried out using R [7], which is a language and environment for statistical computing and graphics. R is an open source, free statistical software system that's widely adopted by the data science community. It also has particularly advanced data visualization capabilities.

Two experiments were carried out to analyze the performance and results produced by the K-Means, ckMeans, and FCM algorithms. Both experiments were conducted using the R statistical programming language, using the hardware and software setup described in Table 1. R provides an implementation of K-Means, which was used in this study, alongside the FCM implementation provided by the e1071 R package [13]. The ckMeans algorithm was implemented by the authors, by adapting the FCM source code from e1071.

Table 1 - Testing platform hardware and software configuration.

Device/software	Details/version
CPU	2.2 GH-z 6-Core Intel i7
Memory	16 GB 2400 MHz DDR4
Graphics	Radeon Pro 555X 4 GB
Operating System	macOS Catalina Version 10.15.3
R version	3.6.1 (2019-07-05)

The Experiment A was used an image from the Berkeley Segmentation Data Set and Benchmarks 500 (BSDS500) [14]. This database is widely used in image segmentation studies using a variety of algorithms, such as [15]. The Experiment B was used an aerial image of an urban area (Itapiranga, SC, Brazil) to test the algorithms for remote sensing purposes.

3 Results and discussion

3.1 Experiment A: Bird

Experiment A used the Bird [14] image (Figure 1) from the BSDS500 dataset [15]. In this experiment, the image was segmented using the K-Means, ckMeans, and FCM algorithms. The number of clusters (p parameter) was set to 5 in all cases. Additional parameters were set specifically for the ckMeans and FCM algorithms, as follows: m = 1.25 (fuzziness), ε = 0.01 or max interation = 100 (stop criterion), and a-cut = 0.5 (uncertainty threshold parameter).

Those specific values were chosen based on the results of a set of test simulation runs. For instance, it was found the m parameter value tends to not significantly affect the uncertainty level of the results when clustering raster data, as opposed to tabular data. An ϵ value of 0.01 tends to avoid local minima, and it was found in the test simulations that the system converged satisfactorily with that parameter value.

Finally, an a-cut value of 0.5 represents a low uncertainty threshold, so that only pixels with membership degree higher than 0.5 are classified in a certain cluster. Benchmark tests for each algorithm in segmenting Figure 1 were conducted and can be seen in Table 2.

The benchmark test shows that the K-Means is faster and more efficient memory-wise. Specifically, K-Means is 22x faster than ckMeans, and 32x faster than FCM, on average, while using approximately 35% and 38% of the memory used by ckMeans and FCM, respectively. This is expected, since ckMeans and FCM are

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fuzzy clustering algorithms, while K-Means produces crisp clusters.

Table 2 - Performance of K-Means, ckMeans and FCM in 10 runs.

Method	Time Min (s)	Time Median (s)	Time Total (s)	Memory Use (MB)
K-Means	0.0784	0.130	1.37	22.7
ckMeans	1.65	2.91	33.2	64.4
FCM	3.36	4.15	41.91	58.6

The segmentation process results are shown in Figure 1. Each cluster was manually assigned a color, for better visualization and comparison between outputs. By visually analyzing the output images, it is noticeable the results produced by the K-Means (Figure 1b) and ckMeans (Figure 1c) are similar, while FCM (Figure 1d) produces slightly different results. For example, the image produced by FCM contains more background pixels assigned to 'green' cluster, in comparison to the K-Means and ckMeans images.

The uncertainties in the segmentation process by ckMeans and FCM algorithms are shown in Figures 2, where pixels that were not assigned to any cluster with membership degree higher than 0.5 are represented in pink. It can be noticed the pink pixels are more frequently found in the edges between clusters and in the bird's nest area.

The Figure 3 shows the membership degrees of each pixel in more detail, by algorithm and assigned cluster. In the image, pixels with membership degree above 0.9 are shown in red, identifying areas of the image that were assigned to their clusters with high confidence. Conversely, pixels whose membership degree is below 0.6 are shown in blue, indicating areas where uncertainty is higher. Intermediate values of membership degree (between 0.6 and 0.9) are represented by green, yellow, and orange pixels.

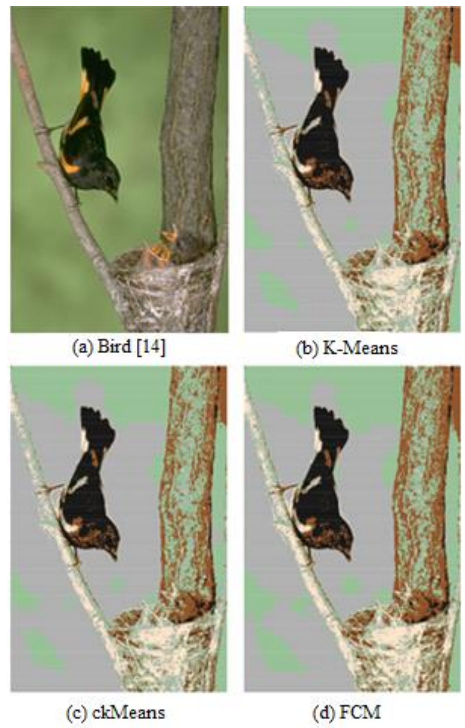

Figure 1 - Bird processing results with different algorithms.

Large groups of red pixels can be seen in clusters 1 and 2 (Figure 3), indicating the high membership degrees of the pixels in those areas. Clusters 2 and 3 presents, visually, the higher number of pixels with membership degrees between 0.7 and 0.9, as indicated by the yellow and orange areas in the image.

Clusters 4 and 5, that covers most of the tree's trunk and branch, as well as the bird's nest, present many red pixels indicating high membership, but those red pixels are rather scattered and do not form solid areas like those in clusters 1 and 2. This can be explained by the blue and green pixels in clusters 2 and 3 that actually belong to the tree and nest, but instead are assigned, with low membership degrees, to those clusters.

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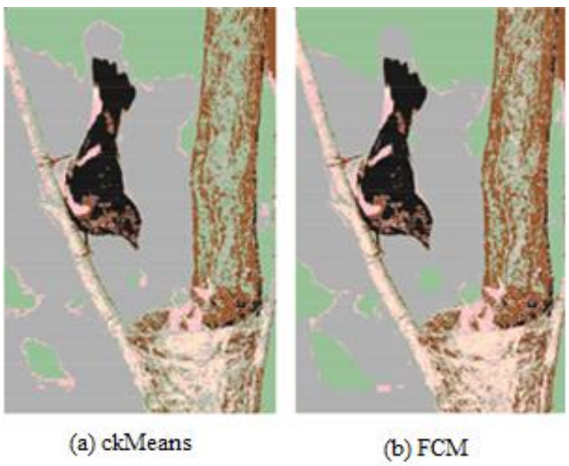

Figure 2 - Clustering with α-cut set to 0.5 of uncertainties.
Fonte: MARTIN et al. [14].

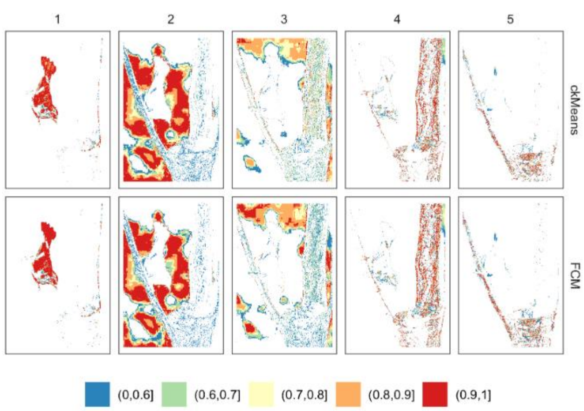

Figure 3 - Membership degree by cluster.

A last quantitative analysis was carried out in Experiment A. The number of pixels in each cluster, grouped by membership degree class, were quantified, and can be seen in the plot of Figure 4. The plot corroborates the previous finding that clusters 1 and, at a lesser extent, 2, have the higher number of pixels with high membership degrees (> 0.9).

Similarly, the uncertainties seen in Figure 3 regarding clusters 3, 4, and 5 can also be seen here, since no bar in the plots of those clusters present a clear predominance over the others. Overall, the results from ckMeans and FCM follow similar trends, apart from a few significant differences. Specifically, those differences seem to be mainly found in cluster 3, which can also be seen in Figure 3.

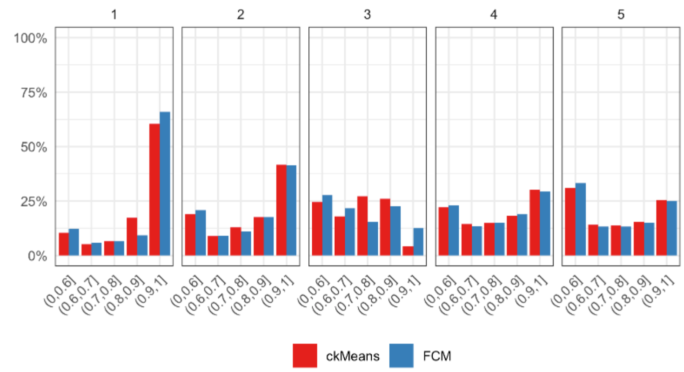

Figure 4 - Percentage of pixels in each membership degree class, by cluster.

3.2 Experiment B: Itapiranga, SC, Brazil

Experiment B used an image from the city of Itapiranga, in the state of Santa Catarina, Southern Brazil (Figure 5). The image was obtained via an aerial photogrametric survey carried out by the state's government in 2010, to be used for planning and research. The use of the ckMeans algorithm for remote sensing purposes was demonstrated by [6], and this paper further explores its potential.

The K-Means, ckMeans and FCM algorithms' parameters used in this analysis were a-cut = 0.6, p = 4, m = 1.75, ε = 0.01. Similarly, to the previous experiment, those parameter values were chosen because they presented better performance in a set of test simulations. Table 3 presents the benchmark results for each algorithm. Corroborating the previous experiment, the results demonstrate that K-Means is faster and less memory-intensive than ckMeans and FCM. Comparing both fuzzy algorithms, ckMeans is 26.3% faster than FCM. Conversely, ckMeans requires 10% more memory than FCM to run.

The segmentation process results are shown in Figure 5. Each pixel's assigned cluster was defined by its largest membership degree and manually assigned a color, for better visualization and comparison between outputs. It is noticeable that all three algorithms produce groupings that are visually indistinguishable to each other. This is in contrast to Experiment A, where a few dissimilarities could be easily identified.

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Table 3 - Performance of K-Means, ckMeans and FCM in 10 runs**.**

Method	Time			Memory Use (MB)
	Min (s)	Median (s)	Total (s)	
K-Means	0,638	1.15	17.3	202
ckMeans	26.2	33.4	323,4	579
FCM	30.3	42.2	412,2	526

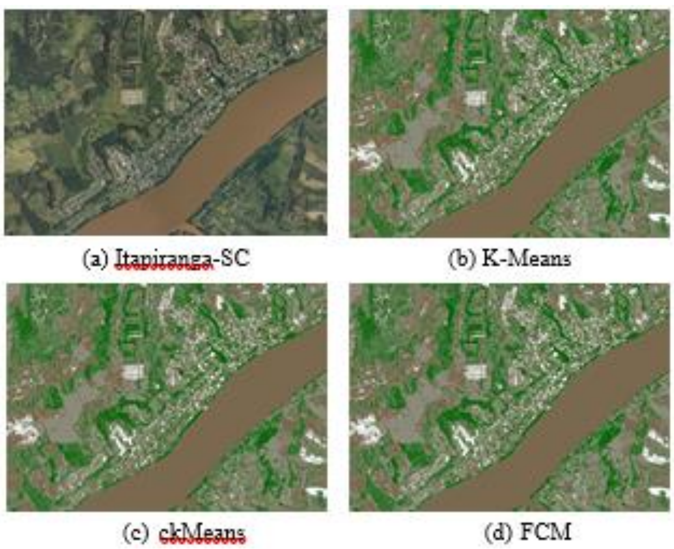

Figure 5 - Itapiranga, SC, Brazil processing with algorithms.
Fonte: Google Earth [16].

Pixels whose membership degree was lower than 0.6 (the *a*-cut parameter value used in this analysis) were assigned the color magenta and can be seen in Figure 6. Those pixels are spread throughout the entire image, apart from the large and homogeneous area covered by the river. Also, they seem to be located mostly in the interfaces between different land-uses, which are areas where lower confidence degrees are expected as the transition between land uses does not occur abruptly in most cases.

The urban area also contains a large number of magenta pixels, which can be explained by the city's low building density and large number of trees on its streets.

Figure 6 - Clustering with α-cut set to 0.6 of uncertainties**.**

Finally, Table 4 shows the percentage of pixels with low membership degrees is similar for all clusters, varying from 7.1% (cluster 3) to 14.8% (cluster 4). This corroborates the previous finding that uncertainties are spread-out in the study area. For all clusters, FCM results present slightly higher number of pixels with low membership degrees when compared to ckMeans.

Table 4 - Percentage of pixels with membership degree lower than 0 in each cluster.

Cluster	ckMeans (%)	FCM (%)
1	7.5	7.9
2	10.6	10.9
3	7.1	7.3
4	14.8	14.3

Previous studies [5] have demonstrated that ckMeans performs better than FCM in classifying tabular data, while this paper presents an exploratory study using raster image data. Although a full validation of the results could not be presented due to the lack of data, the discussion presented here are useful for better understanding the behavior of both algorithms with this kind of data. For instance, similar results were found when using ckMeans and FCM, but the former presents better computational performance than the latter. The levels of uncertainty of FCM found in the experiments presented here are higher than those of ckMeans, but not to a significant degree. Thus, it can be concluded that ckMeans is an interesting alternative to FCM in more time-sensitive situations.

4 Conclusions

K-Means is significantly faster and less memory intensive than the ckMeans and FCM algorithms, which is in line with its wide use in research and practical applications.

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Also, K-Means resulting clusters were very similar to the ones obtained from ckMeans and, to a slightly lesser extent, FCM. However, one important shortcoming of the K-Means algorithm is that it does not take the uncertainties in classification into consideration.

Understanding how those uncertainties manifest in different scenarios is essential to better understand the advantages and shortcomings of each method.

Using the R statistical programming language, which proved to be an efficient way of conducting multiple tests and producing results in a visually compelling manner.

ANÁLISE COMPARATIVA ENTRE K-MEANS, FCM E ALGORITMOS CKMEANS PARA SEGMENTAÇÃO DE IMAGEM

RESUMO: Algoritmos de *clustering* são frequentemente utilizados para segmentação de imagens, com o objetivo de agrupar pixels por sua similaridade e uniformidade. Esse processo é útil para detectar e destacar áreas importantes de uma imagem, facilitando sua análise em diversas aplicações, como no sensoriamento remoto e diagnóstico médico. Este artigo teve por objetivo comparar o algoritmo de hard *clustering K-Means* com os algoritmos *fuzzy clustering* FCM e *ckMeans* em aplicações de segmentação de imagens, utilizando a linguagem de programação estatística R, para análise e visualização dos resultados. A incerteza no processo de agrupamento é discutida por meio do uso do parâmetro alfa-cut. Dois experimentos foram conduzidos, utilizando imagem de um banco de dados aberto e outra imagem aérea de um município Catarinense. Verificou-se que, os três métodos produziram resultados semelhantes, quando considerados os *clusters crisp*. Os resultados de associação difusos de FCM e *ckMeans* também foram comparados e verificou-se que, embora muito semelhantes, *ckMeans* produziu níveis ligeiramente mais baixos de incerteza do que FCM. Ademais, verificou-se que, o *K-Means* apresenta o melhor desempenho computacional entre os algoritmos comparados, o que é esperado devido à sua natureza nítida. Dentre os algoritmos *fuzzy* comparados, o *ckMeans* apresentou melhor desempenho e o FCM exigiu menos memória.

Palavras-chaves: Processamento de imagens. Programação estatística. Sensoriamento Remoto.

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