Image segmentation using fuzzy clustering for industrial applications

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ABSTRACT

This paper presents a fuzzy logic clustering algorithm oriented to image segmentation and the procedure designed to evaluate its performance by varying two parameters: the number of clusters (c) and the diffusivity parameter (m), which leads to the conclusion that an adjusted number of clusters is sufficient to recognize main elements of the image, but a more detailed reconstruction requires a higher number of clusters. Also, the diffusivity parameter influences the smoothness of the boundaries between clusters, low values generate a segmentation with more abrupt transitions and sharper contours, high values smooth the segmentation, its excessive increase may cause the elements to merge, losing details. In general, the balance between these two parameters is key to obtaining an effective segmentation. Three validation scenarios were used, the first two allowed to establish the most appropriate parameters for segmentation, regulating the clusters to a maximum of 4 and keeping the diffusivity level at 2.0, the third scenario validated the algorithm with real images of industrial cleaning products, all with noise, establishing the computational cost and processing times for images of 350×350 and 2000×3000 pixels resolution. In conclusion, applications of the algorithm are foreseen in automatic quality control and inventory control of finished products and raw materials, thanks to its high efficiency and low response time, even in scenarios involving noisy and large images.

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1. INTRODUCTION

Currently, research using fuzzy logic algorithms maintains a strong interest in the scientific community, developing new methods of application of this artificial intelligence (AI) technique [1]–[3]. So that the inclusion of AI under industry 4.0 [4] has adopted fuzzy logic from different fronts such as risk assessment [5], expert-based classification [6], marketing decision strategies [7], and product quality validation [8]. Fuzzy clustering techniques are being employed in applications such as photoacoustic sensor response analysis [9], speech signal evaluation [10], in medicine [11], agriculture [12], and mainly in image segmentation [13]–[15]. Applications of fuzzy clustering are also already industry-oriented: in the determination of load profiles [16], clustering of consumers' big data [17], and tool wear monitoring in micro-milling [18]. Industry 4.0 and 5.0, revolutionized by developments in AI, incorporate among the algorithms used those associated with fuzzy systems [4], [19]. This technological integration allows decision making in intelligent manufacturing processes [20], analytical decision making in intelligent agriculture [21], sustainable logistics [22] and others that enhance the capabilities of the so-called smart factories [23] and homes [24].

With the exposed boom of fuzzy logic and its use in industry, this article shows the implementation and validation of a fuzzy clustering algorithm to determine the segmentation characteristics in images that can be used in industrial environments for identification and/or classification of products. For which the algorithm is implemented in Python language and the parameters of use are established based on the number of groups (c) and variations in the level of diffusivity (m). Thus, determining the features that best fit the identification of industrial cut products, validated with images of cleaners in industrial packaging. This article is divided into four sections, the present state of the art and introduction, the methodology employed, the analysis of the results obtained and finally the conclusions reached.

2. METHOD

The fuzzy c-means algorithm, implemented in Python, is used for image segmentation. This algorithm classifies each pixel of the image into one of the c clusters, assigning a fuzzy degree of membership (m) to each cluster. The process is based on iterative optimization of an objective function and parameter updating, which yields a flexible segmentation that is then reduced to assigning each pixel to the cluster with the highest membership.

The input color image is treated as a set of pixels, where each pixel is represented by three red, green, and blue (RGB) components, this representation allows the image to transform into a data matrix where each row is a pixel, and the columns are the color channels. The membership matrix U of size c×N is randomly initialized where N is the total number of pixels, each element μ_ik represents the degree of membership of pixel x_k to cluster i and is normalized so that the sum of memberships for each pixel is 1 since this way each set of values can be interpreted as a probability distribution. The algorithm seeks to minimize the objective function in (1). Where Q corresponds to the objective function, c is the number of clusters or fuzzy groups whose value is to be determined, N corresponds to the total number of pixels in the image, which can be variable, x_k represents the intensity value of pixel k, μ_{ik} is the degree of belonging of pixel to cluster i, m is the diffusivity parameter and finally, v_i corresponds to the centroid of cluster i.

$$\mathrm{Q} = \sum_{\mathrm{i}=1}^{\mathrm{c}} \sum_{k=1}^{N} \mu_{ik}^{m} \left|\left|\mathrm{x_k} - \mathrm{v_i}\right|\right|^2 \tag{1}$$

The iterative algorithm updates the parameters (centroid of each cluster and degree of pixel belonging to the cluster) in two main steps that alternate until convergence. The first step is the computation of each centroid v_i (2), which is calculated as the weighted average of all pixels, where the weights are the memberships raised to the m power. The second step is the update of the membership matrix, where once the centroids have been calculated, the membership of each pixel to each cluster is recalculated using (3).

$$v_i = \frac{\sum_{k=1}^{N} \mu_{ik}^{m} x_k}{\sum_{k=1}^{N} \mu_{ik}^{m}} \tag{2}$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\left|\left|x_k - v_i\right|\right|}{\left|\left|x_k - v_j\right|\right|} \right)^{\frac{2}{m-1}}} \tag{3}$$

This adjusts the membership of each pixel according to its relative distance to all centroids. It assigns a higher value to the cluster whose centroid is closest. The process of updating the centroids and the membership matrix is repeated until the difference between the membership matrix between two consecutive iterations is less than an error threshold ε=0.005 or a maximum of 100 iterations is reached (parameters defined by the authors).

Once convergence is reached, we proceed to perform image segmentation using two approaches. The segmentation by labels is performed by assigning to each pixel the cluster corresponding to the maximum value of the membership matrix. The resulting vector is reordered to have the same shape as the original image, applying a color mapping that visually represents each cluster with a different color, facilitating the interpretation of the segmentation by labels. In addition, a color segmented image is generated, replacing each pixel of the original image by the color of the centroid corresponding to the cluster to which it was assigned, this is done using the calculated centroids that represent the average color of each cluster. The result is an image in which each pixel adopts the representative color of its cluster, which allows to visually appreciate the grouping of colors in the image. To evaluate the performance of the algorithm, tests were performed on a set of images by varying two main parameters, the number of clusters (c) and the diffusivity parameter (m), to analyze their impact on the variation of the segmentation of each image, following the procedure represented in the flowchart in Figure 1. Tests were conducted using an Intel Core i9 laptop, 24 GB of RAM, and an NVIDIA GeForce RTX 4080 graphics card.

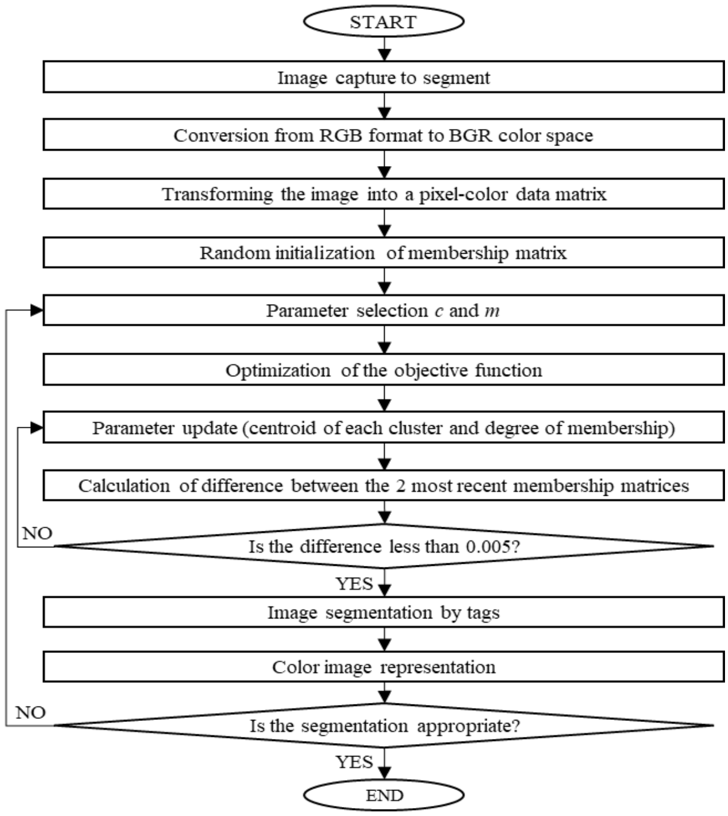

Figure 1. Methodology flowchart

3. RESULTS AND DISCUSSION

The first test image used was a photograph of red flowers on a blue background showing distinct colors [25]. Initially the algorithm was applied with 4 clusters, showing two shades in the sky, the grass and the flowers and a diffusivity parameter of 2.0. The result was a generalized segmentation as shown in Figure 2 where the left part shows the original image, the central part shows the segmentation by labels, and the right part shows the segmentation by centroid colors.

In the segmentation by labels, it is observed that the algorithm separated the most dominant regions of the image as expected. The sky was divided into two areas, which reflects the light gradient present in the original image. The flowers were grouped in a single cluster and the background vegetation was assigned in another, however, due to the reduced number of clusters, the central parts of the flowers that have another color present some mixture with the background vegetation.

This is also evident in the segmentation with colors, which shows a visual simplification in which a general representation of the image is obtained, but with loss of details in smaller elements and subtle changes of the illumination. Additional tests were performed by changing the value of m to 1.5, 2.5, 3.0, however, the results do not show significant changes. For this reason, a new segmentation was performed with 4 clusters and a diffusivity parameter of 5.0 (see Figure 3 where the left part shows the original image, the central part shows the segmentation by labels, and the right part shows the segmentation by centroid colors).

The second test image is a field of sunflowers [26], presenting a more challenging segmentation due to pattern repetition and color similarity between elements. Initially, the algorithm was applied with 5 clusters, differentiating clouds, sky, flower leaves, yellow petals and sunflower centers, and a diffusivity parameter of 2.0 was applied, resulting in a generalized segmentation as seen in the upper part of Figure 4, there, the left part shows the original image, the central part shows the segmentations by labels and the right part shows the segmentations by centroid colors. In this test, some of the main elements are identified, the petals present differences in their tonality, however, the result reveals a deficiency among the plant elements, since the leaves and flower centers are grouped in the same cluster, showing that this configuration is not sufficient to capture all the details that were expected. A segmentation with 20 clusters was tested to evaluate the ability of the algorithm to capture more details and textures in the image. A detailed segmentation is observed in the lower part of Figure 4, where the centroid reconstruction achieves a replica almost equal to the original image.

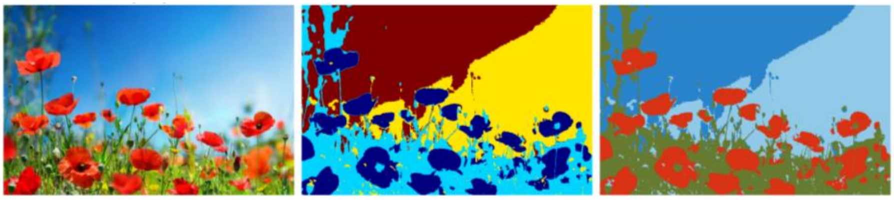

Figure 2. Results first image, c=4, m=2.0

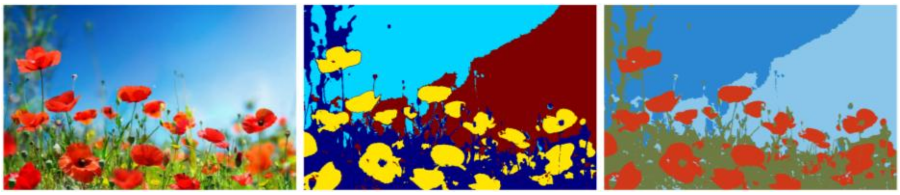

Figure 3. Results first image, c=4, m=5.0

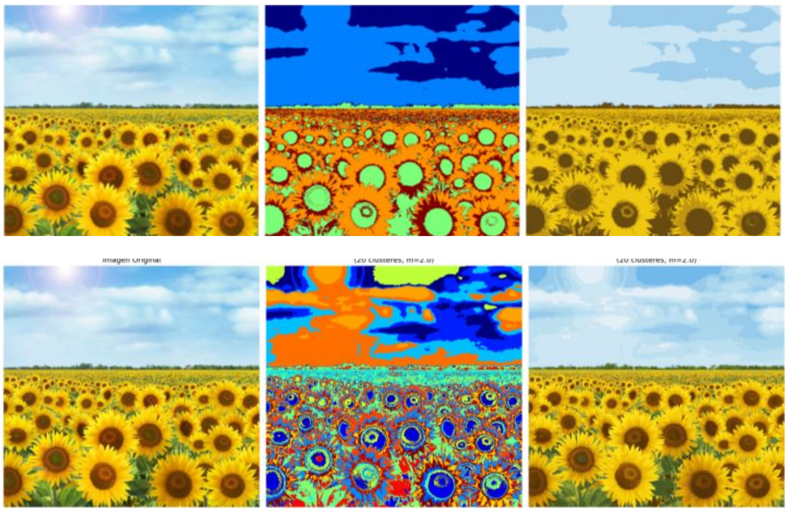

Figure 4. Results second image, c=5 (upper), c=20 (lower), m=2.0

With these previous results and considering that for the algorithm proposed by Huang *et al*. [13] to work well, the number of clusters for an image to be segmented must be predefined, the most appropriate parameters for segmentation are established, regulating the clusters to a maximum of 4 and keeping the diffusivity level at 2.0, given its low impact with small groups, the algorithm is evaluated again with real images of industrial cleaning products with variations from 2 to 4 clusters, as shown in Figure 5. Just as Huang *et al*. [13] and Cui *et al*. [14] used images that include noise in their tests, in this third scenario photographs that reflect light on the surface are used, it can be evidenced that color segmentation allows performing clear product discrimination even under such conditions, with an algorithm of low computational cost, the source file weighs less than 11 KBytes, which is favorable when compared to the image segmentation algorithm proposed by Song *et al*. [15] that does not offer the highest computational efficiency, despite being robust and adaptable. Additionally, the processing times in the classification are in the order 2.53 seconds for images of resolution 350×350 pixels and 4 clusters, using the intuitionistic fuzzy local information c-means (IFLICM) algorithm of Cui *et al*. [14] for this same resolution the segmentation time of each image is higher than 200 seconds, in general the time increases with the resolution of the images, so the algorithm was validated with images of resolution 2000×3000 pixels with times of 3.5 minutes on average, values that contrast with the high time complexity of the algorithm proposed by Huang *et al*. [13]. The results in Figure 6 can be used for label-independent segmentation, which with 3 clusters highlights the product type well and thus facilitates further processing by AI algorithms such as artificial neural networks (ANN) and convolutional neural networks (CNN).

Figure 5. Industrial product segmentation

Figure 6. Label product segmentation

4. CONCLUSION

The number of clusters (c) must be carefully selected depending on the purpose of the segmentation, if the objective is to recognize the main elements of the image, a small number is sufficient, however, if a more detailed reconstruction is sought, it is necessary to use a higher number of clusters, in addition, a too low number can generate loss of essential information. The diffusivity parameter (m) influences the smoothness of the boundaries between clusters, low values generate a segmentation with more abrupt transitions and sharper contours, higher values smooth the segmentation, reducing the contrast between regions, excessive increase of this parameter may cause the elements to merge, losing important details. The balance between the number of clusters and the diffusivity is key to obtain an effective segmentation, since it allows capturing both the general structure and the relevant details of the image. It is possible to conclude that for complex segmentations as presented in the industrial products used, fuzzy clustering facilitates the extraction of characteristics for product identification. Being a complement of support to the techniques of pattern recognition by neural networks or deep learning. After the tests, it is observed that the algorithm presents a low computational cost, reasonable processing times and works adequately regardless of the size of the image and even when it does not have the best quality, so it is proposed as future work the development of applications of the algorithm in automatic quality control and inventories of finished products and raw materials.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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