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Research Article

Fuzzy Clustering Exploiting Neighbourhood Information for Non-image Data

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Abstract: We propose an enhanced variant of the traditional Fuzzy C-Means (FCM) algorithm tailored for leveraging neighbourhood information in non-image datasets residing in Euclidean space. Our novel methodology aims to capitalize on spatial contextual cues inherent in such datasets, thereby complementing the inherent fuzziness of individual data points. Through the incorporation of neighbourhood information, our approach extends beyond the limitations of conventional FCM, leading to improved clustering performance. We validate the efficacy of our method using synthetic and real datasets, demonstrating its superiority over conventional FCM in capturing spatial relationships within the data. Our findings underscore the effectiveness of our approach in enhancing clustering outcomes by strategically incorporating neighbourhood information into the FCM framework for non-image data in Euclidean space.

Keywords: Clustering, spatial FCM, nonimage data, Euclidian neighbour, FCMS.

1. Introduction

In the expansive landscape of clustering methodologies, Fuzzy C Means (FCM) has garnered widespread acceptance, offering a versatile approach to data partitioning [1]. Researchers have routinely leveraged FCM for clustering tasks, showcasing its effectiveness in various applications. Notably, in the domain of image segmentation, the literature abounds with studies employing FCM, with a particular emphasis on exploiting neighbourhood pixel information to enhance segmentation accuracy [2], [3]. However, a conspicuous research gap becomes evident – while FCM with spatial information has been adeptly applied in image-based studies, its application to non-image datasets remains largely unexplored.

The K-means clustering method is known for its simplicity, but it imposes a strict assignment of each pixel to one group only. In contrast, Fuzzy C-Means (FCM) introduces membership degrees, allowing pixels to belong to multiple clusters simultaneously, determined by their membership degrees [4]. While FCM has proven significant in various applications, it has some shortcomings, such as the lack of con- sideration for spatial context in images. This extension renders it vulnerable to noise and imaging artifacts such as intensity inhomogeneity. Additionally, FCM may converge to local optima due to poor initialization [5]. Consequently, modifications have been proposed to enhance its robustness for image segmentation.

Robust FCM (RFCM) using a penalty term into the objective function has been proposed in [6]. Nevertheless, the objective function of RFCM demonstrates intricate variations in the membership function. Another approach, spatial FCM (SFCM), adjusts the membership function by integrating spatial information, showing improved performance but remaining sensitive to serious noise [7].

Fast Generalized Fuzzy C-Means (SFFCM) was proposed where they used spatial information for brain MRI segmentation, yet its performance degrades with significant noise [8]. Maximized fuzzy partition entropy with 2D histogram for MRI segmentation also be used but suffered from high time complexity [9]. Modified versions of FCM have been proposed, including non-local FCM (NL/FCM) and FCM with non-local spatial information, both addressing robustness against noise and inhomogeneity but showing limitations under high noise levels [10], [11].

An updated FCM approach has been developed by changing the objective function to include a Gray-difference coefficient, aiming to enhance performance against noise [12]. These adaptations demonstrate ongoing efforts to address the limitations of FCM in image segmentation, with each method presenting its advantages and trade-offs.

The prevailing trend in the literature underscores a concentration of efforts towards leveraging FCM for image segmentation, where the incorporation of spatial information is pivotal for capturing contextual relationships among neighbouring pixels. Yet, the omission of FCM with spatial information from non-image data analysis raises questions about the algorithm's untapped potential beyond the visual domain.

This research endeavour seeks to address this noteworthy gap in the literature. In our work, we aim to bridge the divide by introducing FCM with spatial information to the realm of non-image data, propelling the algorithm into uncharted territories. By expanding FCM's application beyond the confines of image analysis, our research endeavours to shed light on its adaptability and efficacy in discerning cluster structures within diverse datasets.

There are several works has been done on spatial constraint. Conventional FCM is very sensitive on noise and outliers. To overcome that a deformable strategy is adopted in [13]. They used a neighbourhood window using the form of free deformation. The Fuzzy c-means (FCM) clustering algorithm stands as a prominent technique in both greyscale and color image segmentation, particularly renowned for its efficacy in real-color image processing. Nevertheless, its performance in the extraction of regions of interest often falls short, primarily attributed to the utilization of a singular distance metric in the traditional FCM framework. To address this constraint, researchers have introduced an inventive method called the Fuzzy C-means clustering algorithm based on Super pixel Merging and Multi-feature Adaptive Fusion Measurement (FCM-SM) [14]. An approach incorporating adaptive spatial and intensity constraints, coupled with membership linking, has been suggested to tackle the segmentation challenges posed by noisy images [15]. Kernelization of FCM is another popular method to analyse images to exploit neighbourhood pixel information [16]. Intuitionistic fuzzy set theory based approach also be there to exploit spatial constraint [17]. In all the literature, they exploit neighbourhood information in spatial domain.

The novelty of our work lies in the exploration of spatial information as a guiding principle for cluster formation in non-image datasets. Recent studies have suggested that spatial relationship, albeit abstracted from pixel neighbourhoods, play a crucial role in understanding the inherent structure of diverse data types [18], [19]. This departure from conventional FCM applications opens avenues for uncovering hidden patterns and relationships that may have been overlooked in conventional clustering approaches.

As we embark on this exploration, the potential impact of our work extends beyond a mere methodological innovation. The introduction of FCM with spatial information to non- image data analysis not only broadens the algorithm's applicability but also holds promise for unveiling nuanced cluster structures in datasets.

To illustrate our idea, we take a synthetic dataset first and address the problem to find a true cluster structure using FCM. Then, we take the spatial information to solve that issue. We also study real datasets as well. In the following, we discuss the FCM algorithm with spatial information in section 2. Next, we describe the results in section 3. Discussion of the result is in section 4. In section 5, we have the conclusion and future scope.

2. FCM with spatial information

The FCM objective function to cluster a dataset

$\{x_k\}_{k=1}^{n} \subset R^d$ is represented as [1]

$$J_m = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} \, ||x_k - v_i||^2 \quad (1)$$

where c stands for clusters and n is the number of samples. $\|\cdot\|$ stands for the Euclidean norm. The function is minimized under the following constraints:

- C1: $u_{ik} \in [0,1] \quad \forall i, k$
- C2: $\sum_{i=1}^{c} u_{ik} = 1 \quad \forall k$
- C3: $0 < \sum_{k=1}^{n} u_{ik} < n \quad \forall i$

In Equation 1, J_m provides a good result when the clusters are well grouped and separated from one another. Consider a dataset where the clusters are not well separated, rather one cluster is gradually approaching to other (Figure 1). In Figure 2, we have shown the result for two clusters for m = 1.5. It is noted that FCM could not find the natural cluster structure. So the proximity of the data is not preserved in FCM. Then, why FCM fails here? The reason is, FCM works on the principle of sum of squared error where the distance of each sample is measured from the centre of each cluster. The points that are closer to a cluster centre, their membership values for that cluster are higher. So, from Figure 2, the misclassified data points (marked in red in the green cluster) are much closer to the cluster centre marked in red compared to the green cluster. Therefore, the FCM algorithm could not preserve the proximity of the data points in a cluster. This scenario often occurs due to outliers and raises challenges in understanding and assessing clustering results.

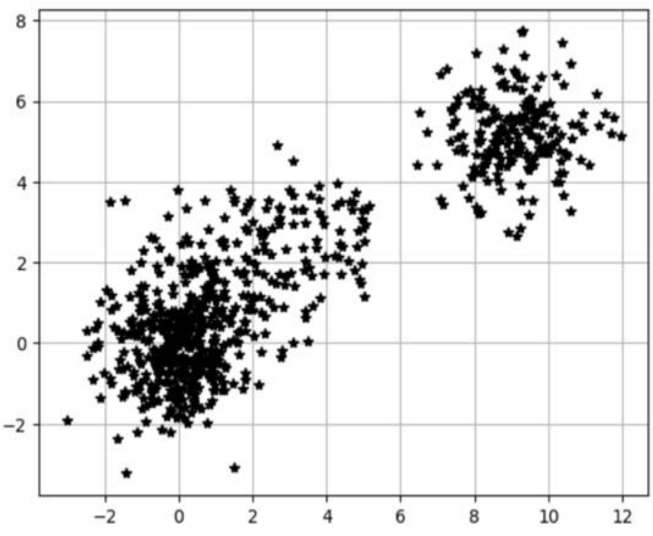


Figure 1. Synthetic dataset

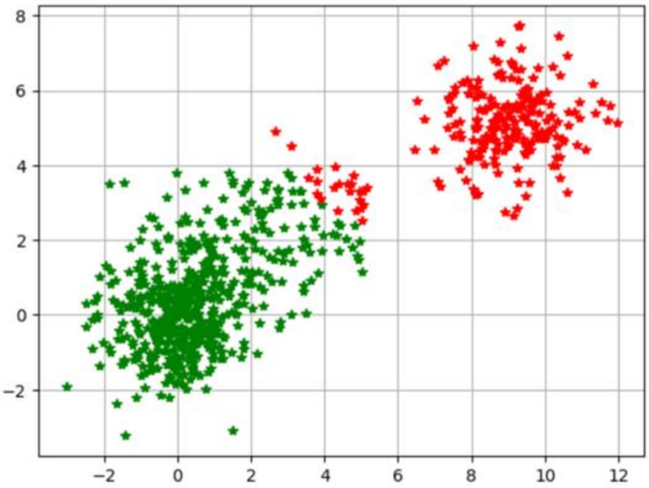


Figure 2. Clustering using FCM (c=2, m=1.5)

In [20], a technique is proposed to enhance the robustness of the standard Fuzzy C-Means (FCM)algorithm by adding a penalty term with the objective function of FCM as below:

$$J_m = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m}\ ||x_k - v_i||^2 + \frac{\propto}{N_R}\sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m}\sum_{r\in N_k}||x_r - v_i||^2 \quad (2)$$

where N_k is the set of neighbours of x_k and N_R is its cardinality. Note that, the first term is the conventional FCM. The second term is the penalty term to exploit the neighbourhood information. The effect of the penalty term is controlled by the parameter α. Increasing the value of α, we give more emphasize on the penalty term. The penalty term is added to exploit the spatial constraint so that the continuity on neighbouring pixels around x_k is maintained. The objective function can be minimized under the same constraints as standard Fuzzy C-Means. Note that, in [20], they have used it to segment image data, as in image we have the advantage to get the neighbouring information in terms of pixels. In [20], [21], they have used $||x_r - v_i||^2$ to measure the spatial distance in an image. Here, we use the Euclidian distance to capture the spatial information. In Figure 1, we do not have such pixels information, still we use the model proposed in [20] to exploit the spatial information.

Using Lagrange multiplier, u_{ik} of the k-th sample to the i-th cluster can be deduced as:

$$u_{ik} = \frac{\left(||x_k - v_i||^2 + \frac{\propto}{N_R}\sum_{r\in N_k}||x_r - v_i||^2\right)^{-\frac{1}{(m-1)}}}{\sum_{j=1}^{c}\left(||x_k - v_j||^2 + \frac{\propto}{N_R}\sum_{r\in N_k}||x_r - v_j||^2\right)^{-\frac{1}{(m-1)}}} \quad (3)$$

Equation 3 is derived using the first order necessary condition of optimality with respect to U, i.e., by setting the first order derivative of Equation 2 with respect to zero.
The expression of the prototype can be shown as

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m}\left(x_k + \frac{\propto}{N_R}\sum_{r\in N_k} x_r\right)}{(1+\propto)\sum_{k=1}^{n} u_{ik}^{m}} \quad (4)$$

Equation 4 is obtained from the first order necessary condition of optimality of J_m with respect to **v**.
We call this algorithm as FCMS (FCM-Spatial) and the corresponding algorithm is shown in Algorithm-1.

Algorithm 1: FCMS

1. Fix c (no. of clusters), t_{max} (no. of iteration), m>1 and $\epsilon > 0$,
2. Initialize u
3. For t=1,2, …, t_{max} do
   Update $v^{t+1} = [v_{ik}^{t+1}]_{cxd}$ using to equation (4)
   Update U=$[u_{ik}]_{cxn}$ uing to equation (3)
   until
   $$\sum_{i=1}^{c}\sum_{k=1}^{n}\left|u_{ik}^{(t+1)} - u_{ik}^{(t)}\right| < \epsilon \quad (5)$$
   is satisfied.
4. Return V and U.

In the following section, we utilize both synthetic and real datasets to evaluate the model performance. We again emphasize that we exploit the model on non-image data and use the proximity of the sample to assign a cluster label. As per our knowledge, the model is only used so far on image data to use the neighbourhood pixels information.

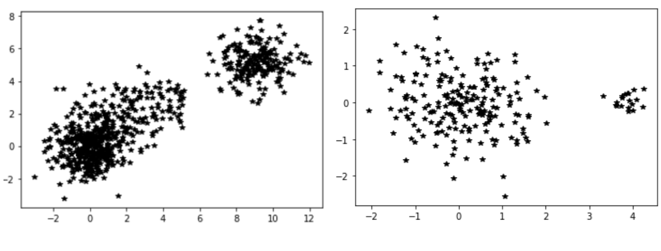
3. Results and Discussion

We have conducted experiments on two synthetic datasets and four real datasets. First, we use two synthetic datasets: Data Set-1 (Figure 3a) and Data set-2 (Figure 3b), all in R^2 because the ground truth of such datasets is known. So, we can visually examined the output. Finally, we have studied the performance on four real datasets (Table 5).

3.1 Studies on the synthetic datasets

To analyse the performance of the model (Equation 2), we first consider two synthetic datasets as below:

Data Set-I: Figure 3a represents the Data Set-1, which contains two clusters out of which one is gradually approaching to the other. The bigger cluster contains 547 points and the smaller one contains 201 points.
Data Set-II: Figure 3b displays the Data Set-II. The datapoints for the two clusters are 200 and 20 respectively.



(b) Dataset-I (a) Dataset-II

Figure 3: Synthetic datasets used in the study

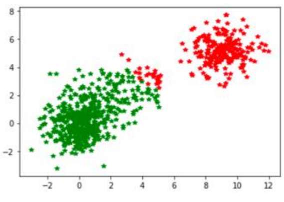
In all the clustering output, distinct clusters will be visually represented using separate colours. We study the effect of FCM and FCMS on Data Set-I and II. To generate the results, we use m = 1.5 and 2, $\epsilon = 10^{-5}$, $\mathbf{t_{max}} = 100$.

First, we consider the Data Set-I (Figure 3a). In the data set two clusters are there and one cluster is gradually approaching to the other. We first examine the behaviour of the FCM algorithm. The result is shown in Figure 2 for m=1.5. Note that, here FCM fails to find the natural partition. As discussed already, it is due to the fact that the proximity of a sample is not preserved in FCM. We clearly see that points from the green cluster which are close to the red cluster are miss clustered. We have tested the result for several run as well as for different fuzzifier (m).

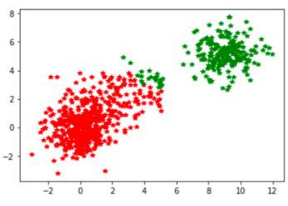
Now, we apply the FCMS algorithm on the same data set. We study the behaviour of FCMS with the following parameters:

- m = 1.5, 2
- α = 2, 3
- N_k = 10, 15, 30, 50, 80

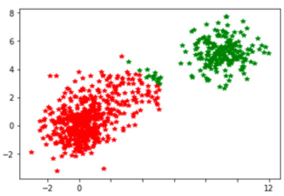
In Figure 4, we have shown the results of different clusters for m= 1.5, α = 2 and N_k = 10, 15, 30, 50, 80. It is seen that, with the increase of the neighbours there is an improvement in the clustering result. If we compare Figure 4a with Figure 4e, it is easily seen that in Figure 4e the proximity of the data points is well preserved. The number of misclassification is reduced when N_k = 80. To provide a quantitative evaluation of the clustering outcomes, we use Normalized Mutual Information (NMI) [22] and Adjusted Rand Index (ARI) as the cluster validity indexes [23], [24]. High values of NMI & ARI indicate better clustering results. Maximum value of both the index is 1. In Table 1, we summarise the results. It is observed that both the indexes increase with the number of neighbours (N_k). It is noted that in spite of increasing the neighbour, we could not get the proper cluster as one point is still miss-clustered. To overcome that, we go for the hard clustering by setting m = 1.01. The corresponding result is shown in Figure 5 and the NMI and ARI in Table 1.



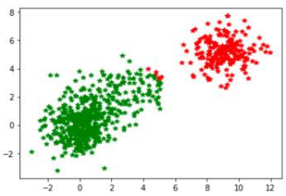
(a) N_k=10



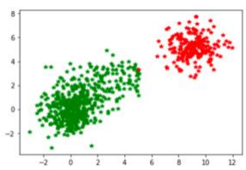
(b) N_k=15



(c) N_k=30



(d) N_k=50



(e) N_K=80

Figure 4: FCMS with no. of clusters=2, m = 1.5 and α = 2

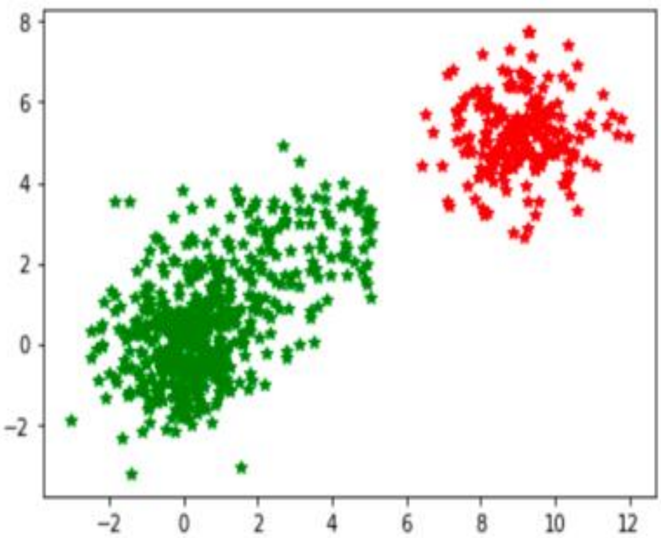
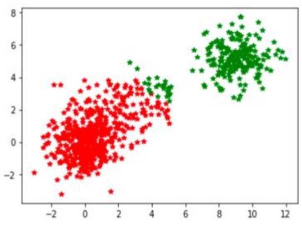


Figure 5: FCMS with no. of clusters=2, m = 1.01, α = 2 and N_k = 50

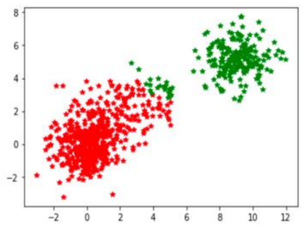
Table 1: NMI & ARI using FCMS for different selection of N_k. Number of clusters =2 and α=2.

m	N_k	NMI	ARI
1.5	5	0.85	0.91
	10	0.87	0.92
	15	0.87	0.92
	30	0.88	0.93
	50	0.97	0.98
	80	0.98	0.99
1.01	50	1.00	1.00

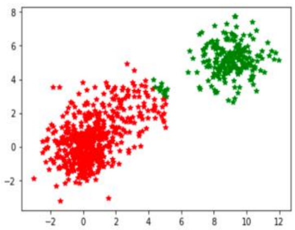
To check the sensitivity of the hyper-parameters, we have studied the effect of the neighbours on the Data Set-I (Figure 3a) for (m = 1.5 & α = 3), (m = 2 & α = 2) and (m = 2 & α = 3). The outcomes corresponding to these parameters settings are depicted in Figure 6, Figure 7, and Figure 8 respectively.. The NMI and ARI of the above combination are noted in Table 2, Table 3 and Table 4 respectively. In all the cases it is obvious that the proximity of the data is preserved while clustering.



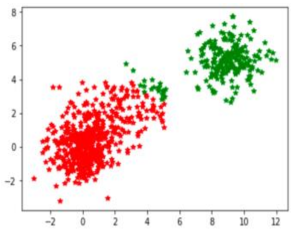
(b) N_k=10



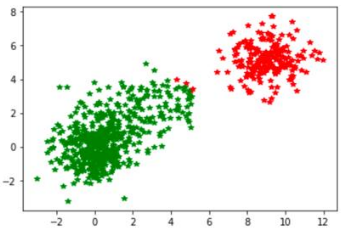
(a) N_k=15



(d) N_k=30

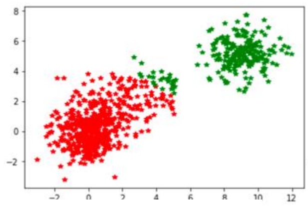


(c) N_k=50

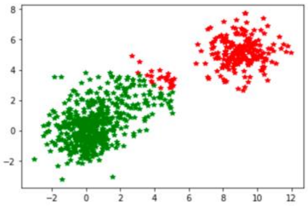


(e) N_k=80

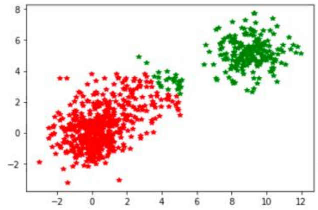
Figure 6: FCMS with no. of clusters=2, m = 1.5 and α = 3



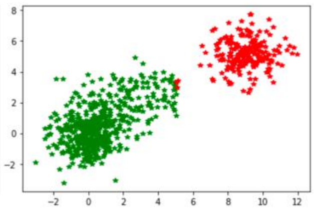
(b) N_k=10



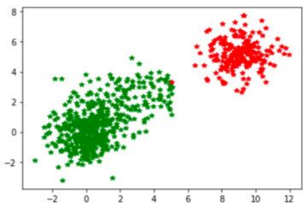
(a) N_k=15



(d) N_k=30

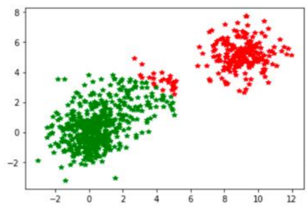


(c) N_k=50

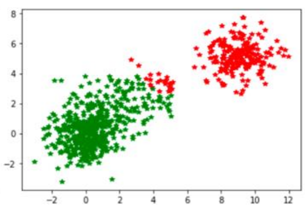


(e) N_k=80

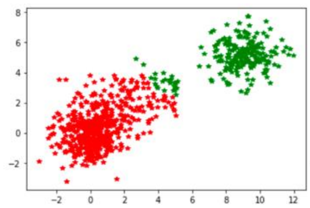
Figure 7: FCMS with no. of clusters=2, m = 2 and α = 2



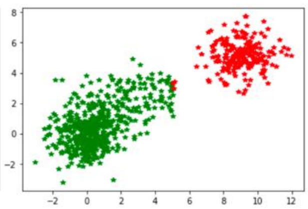
(a) N_k=10



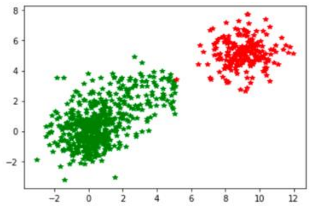
(b) N_k=15



(d) N_k=30



(c) N_k=50



(e) N_k=80

Figure 8: FCMS with no. of clusters=2, m = 2 and α= 3

In Equation 1, J_m serves as a suitable criterion when the clusters exhibit compact, well-separated formations. However, a less apparent issue arises when there are significant variations in the sample numbers across different clusters. Under such circumstances, a partition favoring the splitting of a large cluster may be preferred over one preserving the natural cluster integrity. To illustrate that issue, we take Data Set-2 (Figure 3b). First, we implement FCM with m = 1.5 and 2. The corresponding result is shown in Figure 9. It is clear that the result is not intuitive. In both the cases FCM fails to find the proper clusters.

Now, we have implemented the FCMS on Data Set-II. The result is shown in Figure 10a. It is noticed that for m = 1.5, α = 2, and N_k = 5 (Figure 10a) and m = 2, α = 2, and N_k = 20 (Figure 10b), FCMS produces intuitive result. It is noted that, for a higher value of 'm', the number of neighbours is more to get the proper cluster.

3.2 Studies on real datasets

We use real dataset from the UCI Machine Learning Repository. We take four datasets as listed in Table 5. The parameter we have used in FCMS algorithm for each dataset is tabulated in Table 6. All the combinations of each parameter (m, α and N_k) as shown in Table 6 for each dataset are evaluated. To compare the result of FCM with FCMS, we cluster the data using FCM with m = 1.5 and m = 2. For better visualization, we have reported NMI by taking all the combinations of the hyper-parameter as shown in Table 6. The corresponding value of NMI is shown in Figure 11. In each figure, last two bars indicate NMI for FCM (one for m = 1.5

Table 2: NMI & ARI using FCMS for different selection of N_k. Number of clusters =2, m=1.5 and α=3.

N_k	NMI	ARI
5	0.85	0.91
10	0.86	0.92
15	0.85	0.92
30	0.87	0.92
50	0.95	0.98
80	0.97	0.98

Table 3: NMI & ARI using FCMS for different selection of N_k. Number of clusters =2, m=2 and α=2.

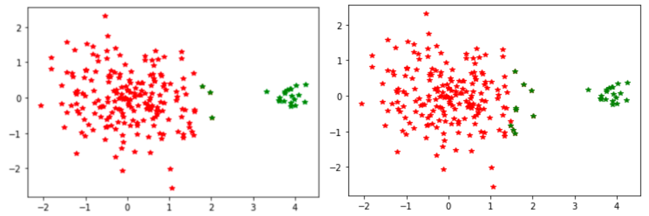
N_k	NMI	ARI
5	0.85	0.91
10	0.86	0.92
15	0.85	0.91
30	0.87	0.92
50	0.95	0.98
80	0.97	0.99

Table 4: NMI & ARI using FCMS for different selection of N_k. Number of clusters =2, m=2 and α=3.

N_k	NMI	ARI
5	0.85	0.90
10	0.86	0.92
15	0.86	0.92
30	0.87	0.92
50	0.97	0.99
80	0.98	0.99

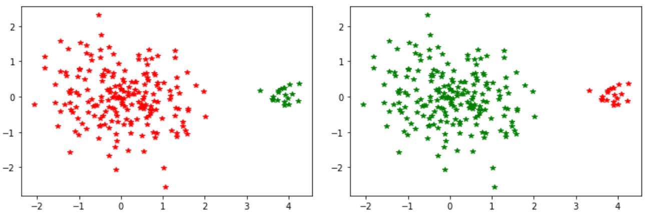
Table 5: Real dataset

Dataset	Instances	Features	Class
IRIS	150	4	3
WINE	178	13	3
MUSK	476	166	2
SONAR	208	60	2



(a) m=1.5 (b) m=2

Figure 9: Applying FCM on Dataset-II with no. of clusters=2



(b) m=1.5, N_k=5 (a) m=2, N_k=20

Figure 10: Applying FCMS on Dataset-II with no. of clusters=2

and other for m = 2) and the rest are for FCMS. The black horizontal line denotes the highest NMI among the two results of FCM, i.e., for m = 1.5 and m = 2. It is seen that in all the dataset, there are many cases, where FCMS outperforms FCM.

Table 6: Study on real datasets for m = 1.5, 2 and α = 2, 3, 5, 7, 10 with different N_k

Dataset	N_k
IRIS	5, 10, 15, 20, 25, 30, 35, 40
WINE	5, 10, 15, 20, 25, 30, 35, 40, 50, 60
MUSK	5, 10, 15, 20, 30, 40, 50, 70, 90, 120, 150, 180, 200
SONAR	5, 10, 15, 20, 25, 30, 35, 40, 50, 70, 90

4. Discussion

FCMS, an extended version of the Fuzzy C-Means (FCM) algorithm, emerges as a solution to the limitations encountered by conventional clustering methods in complex scenarios. While FCM excels in scenarios with well-defined, separated clusters, its performance falters when confronted with datasets exhibiting unclear cluster boundaries or spatial continuity. FCMS is specifically crafted to address this challenge by integrating spatial information, setting it apart from conventional FCM algorithms primarily applied to image data.

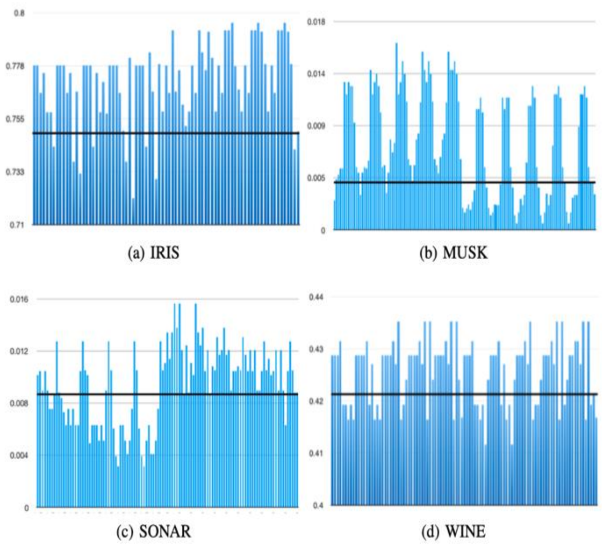


Figure 11: Values of NMI for all combination as shown in Table 6. Black horizontal line indicates the NMI for FCM

Typically, spatially constrained FCM algorithms find their niche in image processing, leveraging spatial information in the proximity of pixels. However, FCMS extends this paradigm beyond the image data, showcasing its adaptability on non-image datasets. The essence of spatial information roves pivotal, especially when dealing with datasets where natural cluster lacks compactness and distinct separation.

The conventional FCM objective function relies on minimizing squared errors based on Euclidean distances between data points and cluster centers. However, FCMS introduces a novel dimension to the objective function—a penalty term. This addition facilitates the preservation of proximity among neighboring pixels or data points, particularly beneficial when handling datasets with less-defined cluster boundaries.

Our experiments, both on synthetic datasets and real-world scenarios, underscores FCMS's efficacy in diverse situations. Notably, in synthetic datasets featuring gradually converging clusters, FCMS outshines FCM by adeptly preserving proximity within clusters.

Parameter sensitivity emerges as a noteworthy aspect, with the fuzzifier (m), penalty parameter (α), and the number of neighbours (Nk) playing crucial roles in fine-tuning FCMS's performance. This adaptability ensures the algorithm's applicability across various dataset characteristics.

5. Conclusion and Future Scope

We introduced FCMS, an extension of the FCM algorithm designed to address the limitations of conventional clustering methods in scenarios with complex spatial characteristics.

While traditional FCM excels in well-defined clusters, FCMS incorporates spatial/neighbourhood information to handle datasets with unclear cluster boundaries or spatial continuity.
We have shown that conventional FCM fails to extract the pattern from Figure 2. This paper highlighted FCMS's adaptability beyond image data, showcasing its effectiveness in non-image datasets as shown in Figure 4. The inclusion of a penalty term in the objective function facilitates the preservation of proximity among neighboring data points, proving beneficial in datasets where natural clusters lack compactness. We have shown that we get more intuitive result for N_k=80 then N_k=10. Experiments on synthetic and real-world datasets demonstrated FCMS's efficacy in diverse scenarios and we quantify the results in terms of NMI and ARI. The paper emphasized parameter sensitivity, highlighting the roles of the fuzzifier, penalty parameter, and the number of neighbors in fine-tuning FCMS's performance.

In this paper, our exploration showcased a notable enhancement in clustering performance through the application of FCMS, especially evident in non-image datasets where traditional FCM methods face challenges. By integrating spatial information, FCMS emerges as a valuable tool in the domain of cluster analysis, holding great promise for diverse real-world applications. Our future endeavors aim to broaden the scope by extending the utilization of neighbourhood information to manifold learning. The exploration of geodesic distance in this context serves as a testament to the evolving versatility of FCMS.

Data Availability
On request, synthetic data will be accessable. All the real data is available at https://archive.ics.uci.edu.

Conflict of Interest
Authors do not have any conflict of interest.

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Authors' Contributions
Author-1 involved in data analysis, coding & formatting.
Author-2 researched literature and conceived the idea.

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