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Image Segmentation Based on an Improved Fuzzy Clustering Algorithm

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Extended Abstract

Traditional fuzzy clustering algorithms are considered powerful tools for image segmentation. However, these algorithms face two main challenges. First, they are sensitive to outliers. The fuzzy memberships in these algorithms are non-dispersive, meaning they are heavily influenced by outliers, largely due to the use of squared error in their objective function. This flaw can lead to incorrect and unreliable clustering results, reducing robustness. Second, they tend to produce an excessive number of clusters. Traditional fuzzy clustering algorithms often create too many clusters, many of which are unnecessary and redundant. This phenomenon, known as over-segmentation in fuzzy clustering, occurs due to the image's loss of local spatial information. To address these challenges, this study presents a solution that enhances the robustness of the fuzzy clustering algorithm. The proposed algorithm includes two main components: the first involves adding a Gaussian-based regularizer to the objective function, which incorporates a Gaussian sub-criterion to calculate the distance between data points and cluster centres. By adding this criterion, the proposed method increases the dispersion of fuzzy membership functions, thereby reducing the impact of outliers and improving clustering accuracy. The second component involves using a filter to resolve the problem of excessive clustering. The proposed algorithm was compared with traditional fuzzy clustering methods and spatial information-based methods to validate its performance, yielding superior results. The algorithm achieves higher accuracy and cohesion in image segmentation while being more robust to outliers and noise.

Introduction

Numerous models have been proposed for computer vision applications, including biometric identification, medical imaging, 3D object recognition, autonomous driving, and many more, as a result of developments in vision technologies [1]. Image segmentation is recognized as one of the essential tasks in different computer vision applications. Choosing an appropriate segmentation approach can significantly improve the accuracy of these applications. Image segmentation is the process in which similar pixels are separated based on features such as colour, texture, brightness, and other attributes. In other words, image segmentation is a vital technology in image processing that is a key step from processing to image analysis [2].

Image segmentation can be considered a foundation for a deeper understanding of image content. On the other hand, image segmentation can transform the original image into a more abstract and compact form, allowing for higher-level segmentation and understanding of the image [3]. Image segmentation is a critical component of image processing, primarily focused on dividing an image into multiple segments based on features such as texture, colour, brightness, or contrast according to a predefined criterion known as the objective.

Image segmentation serves as the foundation for advanced analysis, detection, tracking, image understanding, and compression encoding. Accurately

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and efficiently isolating the target image from a complex background is essential, as segmentation precision directly influences the effectiveness of subsequent tasks.

Image segmentation is utilized to separate the foreground from the background, given that this separation at an early stage is crucial for image recognition and comprehension. Major applications where image segmentation plays an essential role include medical image segmentation, satellite image segmentation, infrared image segmentation, and more [4], [5].

While suitable segmentation of background and foreground objects can help separate them, this task is complex—and sometimes even impossible—due to challenges such as noise, distortion, and low contrast. Recent research has shown that various segmentation methods are widely used [5], [6], [7]. These methods include thresholding, edge-based segmentation, region-based segmentation, clustering, neural network-based methods (ANN), and hybrid techniques [8], [9]. Among these, clustering-based methods are recognized as effective and popular for image segmentation [10].

Clustering involves organizing a dataset into groups with high intra-cluster similarity and low inter-cluster similarity, aiming to maximize similarity within groups while minimizing it between groups [11]. In contrast, image segmentation represents a complex, low-level clustering challenge where performance must adjust to variations in image quality influenced by factors like different imaging devices, environmental conditions, and more [12].

However, image segmentation is challenging, especially for images with noise, low contrast, etc. In image segmentation algorithms, noise refers to unwanted data introduced into the primary dataset, which can significantly impact the final output depending on the features and clustering algorithm. Noise can affect various aspects, such as reducing accuracy, altering cluster shape and location, and changing cluster sizes. Consequently, noise reduction in image clustering algorithms is a critical challenge.

One approach used for image segmentation is fuzzy clustering [13]. Clustering generally distinguishes objects or patterns based on similarity criteria, such as Euclidean distance. Similar objects are typically assigned to a single cluster in the clustering process. Clustering is an important tool in pattern recognition and image analysis. Among the different clustering methods, the Fuzzy C-Means (FCM) clustering algorithm is a well-known and popular technique due to its simplicity [14]. The traditional FCM algorithm is a computational method widely used in data clustering analysis. In its standard form, it performs efficiently and effectively for noise-free data. However, data are often subject to transformations and distortions during collection and transmission, which may introduce noise or outliers. These alterations and artifacts challenge the FCM algorithm, potentially reducing its performance. Moreover, the FCM objective function is based on a squared error measure that is unsuitable for non-spherical data distributions. As a result, several modified versions of the FCM algorithm have been developed to enhance robustness against such artifacts.

In this study, we enhance image segmentation by leveraging underutilized image features and advancing fuzzy clustering algorithms. This research introduces significant innovations to fuzzy clustering algorithms, addressing two primary limitations of traditional methods in image segmentation: sensitivity to outliers and over-segmentation.

The first innovation involves incorporating a Gaussian-based regularizer into the objective function of fuzzy clustering algorithms. This integration disperses fuzzy memberships, improving clustering outcomes by reducing the influence of noisy features. As a result, the method effectively mitigates sensitivity to outliers and handles non-spherical data, which has been a fundamental challenge in traditional FCM algorithms.

The second innovation employs a connected component filter based on regional density balance to alleviate over-segmentation. Unlike complex, time-intensive methods that embed local spatial information into objective functions, this approach is more efficient and rapidly removes small, irrelevant regions. Together, these two advancements significantly improve image segmentation results and enhance the accuracy and efficiency of fuzzy clustering algorithms.

In the following sections of this paper, we provide a comprehensive structure for understanding our approach. Section 2 reviews related work and discusses previous research in the field. Section 3 presents our proposed algorithm in detail. Section 4 focuses on the experimental results and analysis. Finally, Section 5 offers conclusions and recommendations for future research directions.

Related Works

Fuzzy clustering is a method in which each data point can belong to multiple clusters simultaneously. In traditional clustering methods, each data point is assigned exclusively to a specific cluster, with its membership to other clusters being zero. However, in fuzzy clustering, each data point is assigned a membership degree to each cluster, with values ranging between zero and one. Fuzzy clustering has various applications, including data classification, image segmentation, pattern recognition, and natural language processing. Fuzzy clustering demonstrates optimal performance in image segmentation due to its fundamental characteristics [15]. This method offers high flexibility in modelling data, allowing image points to simultaneously belong to multiple clusters, which is particularly effective in addressing the complexities inherent in diverse images. Among clustering methods, the FCM algorithm is one of the most popular clustering techniques used in image segmentation. FCM is an unsupervised classification algorithm designed to partition data into distinct subsets based on their features[16].

Although FCM represents a significant improvement over earlier clustering algorithms, it still encounters challenges such as suboptimal clustering of images affected by noise, outliers, and other artifacts. The most substantial issue is that the segmentation results produced by FCM heavily rely on the choice of cluster centres, the number of selected clusters, and the distance metric employed. Consequently, several enhancements have been proposed to address these limitations[17].
Building on this work, the researchers in [18] proposed a Non-Pure Dense Fuzzy C-Means (DSFCM) that employs a constraint-based denoiser to reduce BCFCM's deficiencies significantly. While DSFCM can provide accurate clustering centres, it is sensitive to denoising parameters, resulting in low robustness. Inspired by the sequential network presented in[19]، the researchers in [20] further explored correlation-based regression and proposed the Membership Correlation Dense Regression (MalFCM) for fuzzy clustering. MalFCM yields better classification results compared to DSFCM; however, due to the use of the Alternating Direction Method of Multipliers (ADMM) [21] for optimizing the correlation matrix, it requires high computational complexity. Nonetheless, both DSFCM and MalFCM depend on the condition that the sum of membership values for each pixel equals 1. To mitigate this constraint, the researchers in [14] introduced a Possible Fuzzy C-Means (PFCM) that combines the concepts of memberships and their possibilities, integrating FCM and Possibilistic C-Means with a softer constraint on memberships. Although PFCM [22] can extract richer informational descriptions from the data, it exhibits poor robustness against non-spherical distributed data. To address this issue, the researchers in [23] proposed a similarity measurement-based method. A Membership Scale FCM (MSFCM) based on the triangle inequality was described by Zhou et al. [24]. MSFCM successfully improves the model's rate of convergence while maintaining the data's clustering accuracy. The authors of [25] proposed a Fast and Robust FCM (FRFCM) based on morphological reconstruction and membership filtering. FRFCM achieves good classification results for various types of grayscale images and has a short execution time.

The choice of the fuzzification exponent plays a crucial role in determining the performance of Fuzzy C-Means (FCM) algorithms for image segmentation tasks. Although it is often set to a fixed value of 2, this parameter can significantly impact clustering results. The sensitivity to the fuzzification exponent necessitates the development of algorithms that can dynamically adjust its value or mitigate its influence on the segmentation outcome.

Further advancements in FCM algorithms have been achieved by integrating relative entropy and kernel distance into the objective function. These modifications aim to enhance the algorithms' adaptability to various image characteristics and segmentation challenges.

However, a persistent concern regarding entropy-based FCM algorithms is their potential for misclassifying outliers due to the lack of consideration for membership density. Xenaki et al. [26] addressed this issue by introducing density criteria in the objective function, demonstrating that density can effectively counteract the effects of closely situated clusters and reduce misclassification. Chen et al. [27] further validated the benefits of density by confirming its capability to prevent performance degradation in clustering algorithms.

Proposed Method

In this study, we introduce modifications to the traditional FCM algorithm in a two-stage process designed to overcome its inherent limitations. Initially, the algorithm incorporates Gaussian-based regularization methods to function as a sparse fuzzy clustering technique, which is effective for obtaining sparse fuzzy memberships. The updated algorithm, leveraging regularization methods, successfully produces the dispersed fuzzy memberships required for precise clustering.

Following this, we apply a density-balancing strategy to merge small, insignificant regions. This implementation allows the proposed algorithm to effectively mitigate sensitivity to outliers and reduce over-segmentation, thereby enhancing the segmentation results.

Error! Reference source not found. further illustrates the differences and similarities between the improved and traditional FCM algorithms. As illustrated in Figure 3, the base algorithm undergoes modifications in two stages. These two stages, called FCM optimization based on regularization for sparse clustering and reduction of over-segmentation through applying a filter, are detailed in the following sections.

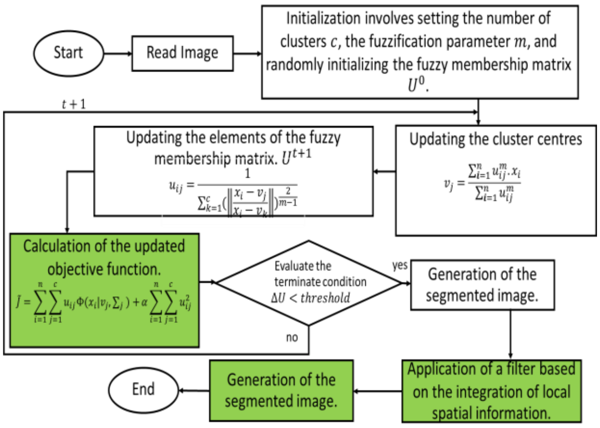

Fig. 1. Steps of the Proposed Method

Based on the analysis presented in the previous chapter, the DSFCM [18], MalFCM [20], and MEFCM [28] algorithms are unable to achieve sparse fuzzy membership functions. A squared error function in these algorithms' objective functions makes them sensitive to outliers and non-spherical data. To address this, the proposed algorithm integrates a Gaussian-based regularizer into the objective function of fuzzy clustering algorithms, enabling it to achieve sparse clustering. This integration ensures the dispersion of fuzzy memberships, effectively reducing the impact of noisy features and enhancing clustering results. Therefore, we introduce a novel regularization approach that incorporates u_{ij} as a cost term. Consequently, the objective function is defined as follows:

$$\tilde{J} = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}\Phi(x_i|v_j,\Sigma_j) + \alpha \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^2$$

In this expression, $\Phi(x_i|v_j,\Sigma_j)$denotes the distance function between x_i and v_j, with α acting as a balancing factor to regulate the sparsity of membership functions. Adjusting α, allows the objective function to exhibit varying levels of robustness against outliers or noisy data.

When the fuzzy membership is sparse in this equation, the first term $\tilde{J}$ will be relatively small, while the second term will be larger. The proposed algorithm typically requires more iterations than k-means to reach optimal calculations but fewer iterations compared to FCM.

Clearly, the new objective function $\tilde{J}$ achieves a balance between k-means and FCM. The resulting fuzzy memberships are sparser than those produced by FCM. Unlike k-means, some fuzzy membership values are not exactly 0 or 1. The distance function $\Phi(x_i|v_j,\Sigma_j)$ is defined as follows:

$$\Phi(x_i|v_j,\Sigma_j) = \ln(-\rho(x_i|v_j,\Sigma_j)) \qquad 1$$

To achieve image segmentation, pixel classification is employed, where each pixel in the image is treated as an independent sample. Consequently, FCM often results in over-segmentation, producing many small, disjointed regions in the segmentation output. Due to inappropriate scatter deviation, DSFCM[18] misclassifies pixels more frequently than FCM and MEFCM[28]. Although our proposed algorithm partially reduces the interference of non-uniform pixels and achieves improved visual quality, it does not fully prevent the over-segmentation issue. Conversely, enhanced FCM algorithms incorporating local spatial information can alleviate over-segmentation by removing small regions, yet this approach alone remains insufficient.

As we know, the mean-shift method can effectively reduce over-segmentation by eliminating small regions with fewer than M pixels, though the value of M is often manually adjusted for different images. In the current paper, we apply a connected component filter algorithm based on a true density-balancing strategy to enhance the proposed algorithm's performance in mitigating over-segmentation. The initial results show numerous small, redundant regions that reduce final segmentation accuracy.

With the proposed filter, we first calculate the area of all connected components and then sort these components in descending order. Since determining an appropriate threshold value Mmerging regions based on this ordering is challenging, so we employ a density-balancing strategy to improve the sorting outcome. This enhancement allows for easy identification of the maximum interval corresponding to a region whose area is considered as the M threshold. Regions with areas above this density-balancing threshold are identified for elimination. After establishing an optimal threshold M, connected components smaller than the obtained M can be removed. We effectively locate the cut-off region through this process using the density-balancing strategy.

Results

This section will describe the evaluation metrics and the dataset used and then examine the results.

The Berkeley Segmentation Dataset (BSDS500) [29] is widely utilized in computer vision, designed for edge detection and image segmentation tasks. It contains 500 carefully labelled images of various sizes collected from diverse sources like movies, digital media, and medical imaging. Divided into training and testing sets, BSDS500 provides a reliable standard for evaluating segmentation algorithms and has become a popular open-source tool for computer vision research. Each image includes multiple human-annotated ground truth segmentations, offering precise pixel-level labels essential for developing and benchmarking segmentation methods. Fig. 2 shows some examples of images from this dataset.

Fig. 2. Examples of images in BSDS500

The Microsoft Research Cambridge Dataset (MSRC) consists of 591 images, each in vertical or horizontal orientation, and supports 23 object classes, enhancing diversity for object detection tasks. A notable feature of this dataset is its use of two-colour spaces: images are originally in RGB format, while test images are converted to CIELAB, a colour space designed to align with human colour perception. This conversion aids object detection algorithms in distinguishing objects based on perceptually accurate colours, improving detection precision.

The evaluation metrics introduced to assess the accuracy of the proposed algorithm are as follows:

Probabilistic Rand Index (PRI) The Probabilistic Rand Index (PRI) is an evaluation metric used in image segmentation to measure the degree of agreement between an algorithm’s segmentation output and the ground truth. PRI considers the number of pairs that are consistently classified in both segmentations. It has two main components: True Positives (TP), which is the count of pairs that belong to the same category in both the algorithm's segmentation and the ground truth. Mixed Pairs (False Positives + False Negatives, FP + FN): The count of pairs that are categorized differently in the algorithm's result and the ground truth. The PRI is calculated as:

$$PRI = \frac{TP}{TP + FN + FP} \quad 2$$

Its value ranges from 0 to 1, where 1 indicates complete agreement, and 0 indicates no agreement.

The Coverage Index (CV) is another evaluation metric in image segmentation, which calculates the ratio of pixels that belong to the same category in both the algorithm's segmentation and the ground truth. It is computed as:

$$CV = \frac{2|S_A \cap S_B|}{|S_A| + |S_B|} \quad 3$$

where S_A is the initial segmentation and S_B is often the ground truth. Higher CV values, between 0 and 1, indicate greater agreement.

Variation of Information (VI) is another metric for evaluating image segmentation. It measures the amount of information one segmentation provides to describe another and vice versa. First, a joint information matrix between the two segmentations is calculated, followed by co-occurrence values across categories. VI is then calculated as:

$$VI = H(A) + H(B) - 2I(A, B) \quad 4$$

where H is entropy and I represents mutual information. VI values range from 0 to $\log N$ with lower values indicating higher agreement between segmentations.

Our experiments utilize three performance metrics to assess segmentation accuracy across different algorithms: Probabilistic Rand Index (PRI), Coverage (CV), and Variation of Information (VI). Higher PRI and CV values, along with a lower VI value, indicate segmentation results that closely align with the ground truth. For our tests, the number of clusters per image in the BSDS500 dataset ranges from 2 to 6, while for images in the MSRC dataset, it ranges from 2 to 4.

We select the set of parameters corresponding to the highest PRI value as the final performance criteria for each image. Fig. *3* and Fig. 4 display the average PRI, CV, and VI values across all images in the BSDS500 or MSRC datasets. A comparison of values in Fig. *3* and Fig. 4 shows that PFCM yields lower performance metrics, as it is sensitive to parameter settings. The proposed algorithm provides the best PRI, CV, and VI values. Analysis of Fig. *3* and Fig. 4 demonstrates that the proposed algorithm delivers high-quality segmentation on various reference images, underscoring its efficiency and stability.

It achieves the highest PRI value of 0.78, indicating superior accuracy compared to the other algorithms. Additionally, the VI value for our proposed algorithm is 2.12, the lowest among all algorithms, indicating less information variation and lower cluster dispersion. Furthermore, this algorithm has a CV value of 0.52, the highest among all algorithms, indicating higher reliability of its clustering.

Based on the results in Fig. *3*, our proposed algorithm performs best on the BSDS500 dataset, achieving top results across all three evaluation metrics (PRI, VI, and CV). The high PRI value reflects greater accuracy, the low VI value indicates less information dispersion, and the high CV value suggests more reliable clustering. This combination of attributes implies that our proposed algorithm is more accurate and maintains the cluster structure optimally.

The performance differences among the algorithms in this table are evident. For example, the PFCM algorithm [22] has a lower PRI (0.72) and a higher VI (2.97) than our proposed algorithm, indicating lower accuracy and greater information dispersion. Although the FRFCM [25] algorithms achieve higher PRI values than other algorithms, they still do not perform as well as our proposed algorithm. Differences in VI and CV values among the algorithms further highlight variations in the clustering approach and cluster reliability.

These results hold significant implications for our research. The superior performance of our proposed algorithm demonstrates its potential to enhance data analysis and clustering that is substantially relevant to our study. With its high accuracy and low information dispersion, this algorithm enables us to obtain more reliable outcomes from data analysis. This, in turn, can lead to improved research quality and increased accuracy of the results.

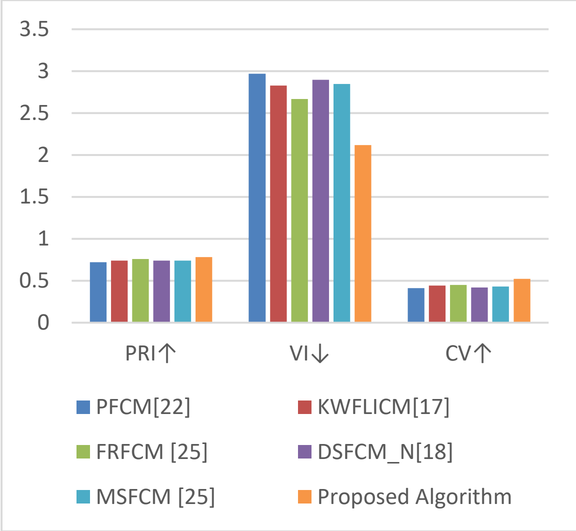

Fig. 3. Comparison of Algorithm Performance on the BSDS500 Dataset

According to Fig. 4, the proposed algorithm demonstrates the best performance among the algorithms evaluated. This algorithm achieves a PRI value of 0.75, the lowest VI value of 1.51, and the highest CV value of 0.64, outperforming other algorithms in terms of accuracy, lower information variation, and clustering reliability.

Due to its higher PRI and CV values and lower VI, this algorithm indicates greater accuracy, less variable information, and more reliable clustering. In other words, the proposed algorithm has effectively clustered the data with higher precision, and the resulting clusters are more reliable with minimal information variance.

Performance differences across the various algorithms are clearly visible in the metrics presented. The PFCM, and KWFLICM[17], with PRI values of 0.67 and 0.69 and a CV value of 0.55, exhibit similar performance. In contrast, the FRFCM algorithm displays different performance characteristics with a CV of 0.58. The MSFCM algorithms also show similar performance in terms of PRI, VI, and CV values.

These findings are particularly meaningful for the research. The strong performance of the proposed algorithm suggests it can perform data clustering with high accuracy and reliability while introducing minimal information variation. This capability is crucial when analyzing complex, large datasets.

The differences in algorithm performance across various metrics (PRI, VI, CV) are notable. For instance, PRI values range from 0.67 to 0.75, VI values from 1.51 to 1.93, and

CV values from 0.54 to 0.64. Such variations reflect differences in accuracy, information variation, and clustering reliability among the algorithms. If these differences are statistically significant, one can conclude that the proposed algorithm performs significantly better than the others.

Clustering with each algorithm can produce different data structures. For instance, algorithms with higher CV values may create more reliable clusters. The algorithms have performed appropriately if these structures align with the defined clustering objectives. Each algorithm may reveal new insights into the data that are highly useful for data analysis.

Overall, algorithms that provide more interpretable and meaningful clustering can greatly benefit research. These algorithms can facilitate better data analysis and lead to improved outcomes.

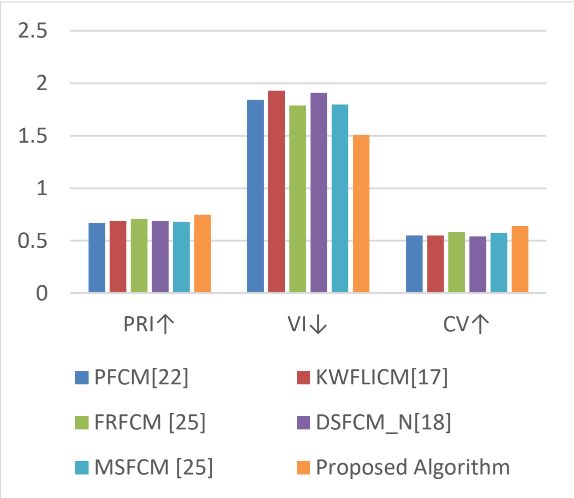

Fig. 4. Comparison of Algorithm Performance on the MSRC Dataset

Conclusion

This study introduces a self-optimizing fuzzy clustering algorithm for image segmentation, addressing two primary challenges in current fuzzy clustering methods. The algorithm incorporates a regularization term to balance cluster scatter and fuzziness, achieving self-regularization, and includes a filtering technique for effective merging of small regions, enhancing segmentation results. Experimental evaluations on synthetic and comparative images demonstrate the algorithm's superior performance over existing methods, with improved segmentation quality and performance metrics. Parameter analysis reveals that clustering effectiveness is maintained when the regularization parameter is below 0.5.

Future research directions include exploring additional algorithm parameters, new filters for merging regions, diverse applications in fields like medical and satellite imaging, and the impact of noise on performance. Evaluating the algorithm on real-world data and comparing it with advanced algorithms could further refine its accuracy, stability, and adaptability in practical scenarios.

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