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Combining Strengths: A Review for Novel Approach to Image Segmentation using Hybrid DBSCAN and the Mumford-Shah Model

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ABSTRACT: Serving as a core pre-processing step, image segmentation segregates an image into homogeneous, spatially connected regions of interest. The individual regions themselves—are fundamental for diverse AI applications, enabling the recognition, matching, and detection of critical features within satellite images, biometric data, and clinical diagnostic scans. The current literature offers numerous segmentation methods; however, the lack of a universal, general-purpose approach highlights a significant challenge in the field, making this area ripe for continued, extensive research. This literature review examines existing methodologies for image segmentation, highlighting the critical need for approaches that simultaneously optimize processing speed, segmentation accuracy, and spatial awareness. The central challenge in the field remains developing a universal method (applicable to any image) that avoids the fragmentation caused by purely color-based clustering techniques. The review specifically evaluates the performance trade-offs of K-means and Agglomerative Clustering, and the benefits of the Mumford-Shah model in ensuring region homogeneity and smooth boundaries. It finds that while prior Mumford-Shah implementations were slow, integrating the model into the Pairwise Nearest Neighbor (PNN) method achieves a superior balance of quality and computational efficiency. This analysis provides the rationale for exploring alternative hybrid DBSCAN clustering techniques with Mumford-Shah model, seeking alternative approaches that might offer similar advantages in balancing efficiency and quality.

KEYWORDS: Image Segmentation, Mumford-Shah Model, Hybrid Clustering, DBSCAN, Computational Efficiency, Computer Vision

I. INTRODUCTION

Image segmentation is a fundamental pre-processing task in computer vision. It partitions an image into distinct regions of interest that exhibit homogeneity and spatial connectivity. These segmented regions represent probable objects and are crucial for various artificial intelligence applications, including the analysis of satellite imagery, biometric pattern recognition, and the identification of pathological areas in medical scans (MRI and X-ray images). While a wide array of segmentation techniques exists in the literature, a universal method applicable to general images across all processing contexts remains elusive, driving continued, profound research in this domain.

Several approaches to image segmentation [1] used by researchers are thresholding, clustering and classification methods [2], [3], [4], region-based methods [5], and edge based active contour methods [6], [7], [8]. The segmentation problem has also been dealt with as an energy minimization problem.

Unsupervised image segmentation which involves obtaining a generalized solution that works without prior knowledge about the object elements, its characteristics like shape, color, texture, appearance of shadows and overlapping of objects, is still an open problem [24].

II. UNSUPERVISED IMAGE SEGMENTATION

Unsupervised image segmentation refers to the task of partitioning an image into meaningful regions or groups of pixels without the use of human-annotated ground-truth labels. Instead of relying on predefined categories, these

methods leverage the intrinsic properties of the data itself, such as color, texture, intensity, and spatial information, to find natural groupings or boundaries.

Unsupervised segmentation methods can be broadly categorized into traditional clustering-based methods like K-means clustering, Mean Shift, Mean Shift. These are a prominent traditional approach where pixels (or super pixels) with similar feature values are grouped into clusters. Also there are graph-based methods such as Normalized Cuts that model an image as a graph where pixels or super pixels are nodes, and edges represent the similarity between neighboring nodes. Segmentation is achieved by optimizing a cost function over the graph.

In the recent past, image segmentation has shifted from traditional methods to deep learning methods. Current research focuses on developing more efficient, accurate, and adaptable models that can operate with less labeled data and handle real-world complexities. Deep Unsupervised Segmentation: Modern approaches utilize deep learning architectures, such as Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), to learn rich, high-level feature representations from unlabelled data.

Classical k-means (KM) clustering for image segmentation

A fundamental category of clustering technique, hard clustering is highly suitable for image segmentation problems, where the primary objective is to divide an image into distinct, non-overlapping regions.

The Classical K-means (KM) [9] algorithm stands out as the most widely used algorithm within hard clustering due to its straightforward implementation and low computational cost, making it particularly effective for managing large datasets like high-resolution images. While the K-means algorithm offers efficiency, it comes with specific limitations. The primary drawbacks noted in literature are:

- a) The requirement that the number of clusters k must be specified as a priori (in advance) [11].
- b) The algorithm's sensitivity to the initial selection of cluster centers, which can result in suboptimal or inferior local minimum solutions.

Fortunately, the research literature provides numerous solutions to mitigate these issues. To address the fixed k parameter, the original minimization function (objective function) can be revised so that the number of clusters becomes a variable solved by the algorithm itself, rather than a fixed input parameter [12]. The quality of K-means results can be substantially improved through better initialization methods and by running the algorithm multiple times (e.g., 100 repetitions) using different starting points and selecting the best outcome [13]. A simple yet powerful modification to further enhance robustness is employing the random swap algorithm. This approach significantly reduces the likelihood of the K-means algorithm getting stuck in an inferior local minimum [14].

Research efforts have led to numerous modifications and enhancements [15], [16], [17], [18] to the standard K-means algorithm. Such adjustments may become unnecessary if an inherently superior clustering algorithm and a correctly defined minimization function are employed from the outset.

Agglomerative clustering

Agglomerative clustering [30], [31] is a powerful hierarchical approach used in unsupervised segmentation as an alternative to methods like K-means. It begins with maximum granularity, where every single data point (pixel or feature vector x_i) is treated as its own individual cluster c_i . The algorithm iteratively merges the two closest or most similar clusters into a single new cluster. This process repeats until a stopping condition is met, typically when a desired number of clusters is reached.

The literature review on agglomerative clustering, specifically focusing on the Pairwise Nearest Neighbor (PNN) method, highlights efforts primarily aimed at improving computational efficiency while maintaining the quality of the clustering results. A variant approach to the PNN method is locally optimal merge (Ward's Method/PNN) [32]. The key to producing quality clusters is how the "closest pair" is defined. Methods like Ward's method select the pair whose merger results in the minimal increase in the overall objective function or variance (minimizing information loss). In the context of vector quantization, this approach is also known as the Pairwise Nearest Neighbor (PNN) method [33]. While it is conceptually simple to implement and does not require the user to pre-specify the final number of clusters in

advance (unlike K-means), its pairwise comparison mechanism means it can be computationally expensive and significantly slower, especially with large image datasets. A detailed review of all the PNN variants is given by this author and the team in [10]. In further developments of the PNN algorithm, a variant known as Lazy-PNN [36] was introduced to significantly enhance speed by employing a strategy of deferred calculations. Practical tests demonstrated substantial performance improvements for the Lazy-PNN, approximately 35% faster than the previously optimized Fast exact PNN variant [38] and 200 to 500 times faster than the original, straightforward implementation of the PNN algorithm [31], [38]. A more general approach called iterative shrinking [41] was proposed to handle the cluster reduction sequence differently. Instead of merging pairs, this method reduces the total number of clusters by systematically removing them one by one. The data vectors that belonged to the removed cluster are subsequently reassigned to nearby, remaining clusters.

The PNN method can actually be viewed as a specialized application of iterative shrinking. The primary difference is the strict constraint in PNN that forces all vectors from a removed "cluster" (or the second cluster in a pair) to be reallocated exclusively to a single, specific neighboring cluster during the merge operation [33].

In yet another approach [42] to accelerate agglomerative clustering, the authors utilized an approximate k-nearest neighbor (k-NN) graph to optimize the process. By structuring the data points in a graph where each cluster only considers its approximate k nearest neighbors, they significantly reduced the total number of merge cost calculations required during the clustering process. All the described variants of agglomerative clustering (Fast exact PNN, Lazy-PNN, and the k-NN graph method) fundamentally aim at improving computational speed. The iterative shrinking method explicitly aims for better quality.

DBSCAN for Image Segmentation

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a clustering algorithm that identifies clusters based on data point density. Fig.1b shows that only DBSCAN algorithm without using spatial connectivity leads to color quantization but can effectively segment images by clustering pixels with similar properties (e.g. color, intensity) that are also spatially close together. Whereas Fig.1c shows that including the spatial connectivity increases outliers.

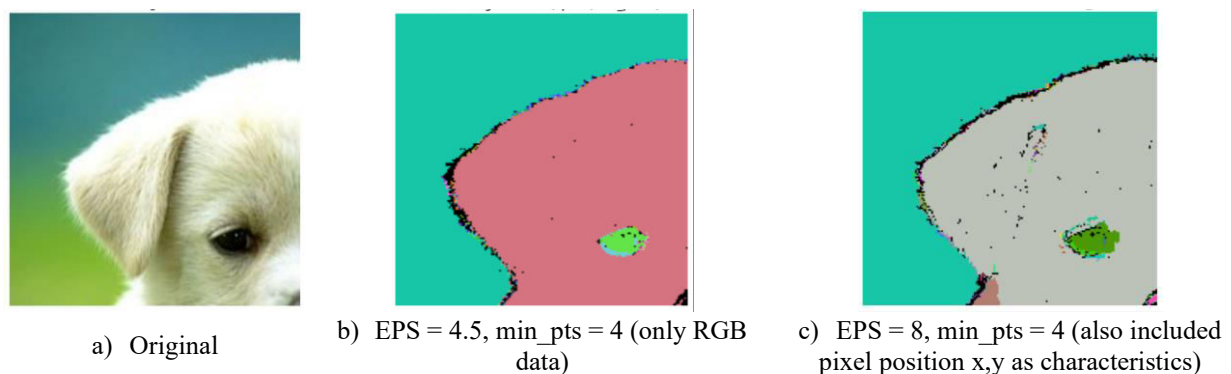


Fig. 1 Results of DBSCAN algorithm using Python

These results are the best (visually) among the many obtained by fine tuning the parameters. Also, the performance is slow. One key advantage of DBSCAN in image segmentation is its ability to handle arbitrarily shaped clusters and identify outliers or noise points, which can correspond to isolated pixels or small, insignificant regions. A challenge with DBSCAN in this context is the difficulty in determining the optimal values for its parameters (epsilon and minimum points), which can impact the quality of the segmentation.

Researchers have developed faster variants of the DBSCAN algorithm. In [51] authors propose an efficient image segmentation method using the TI-DBSCAN density-based clustering algorithm applied directly within the RGB colour space. This novel approach uses the triangle inequality to significantly speed up neighbourhood searches while reducing noise sensitivity and avoiding colour space conversion. A real-time image super pixel segmentation method

operating at 50 frames per second has been proposed, utilizing a two-step framework based on the DBSCAN algorithm. The method involves rapid pixel clustering using colour and geometric restrictions, followed by merging small clusters into super pixels via a robust distance function, achieving state-of-the-art accuracy and efficiency [52].

While standard DBSCAN is effective, Adaptive Parameter DBSCAN [53] overcomes the drawbacks of pre-determining the Epsilon (neighbourhood radius) and minimum number of points parameters by assessing them based on image size and k-dist plots. The experimental results reportedly show significant improvements over existing segmentation methods by substantially reducing image noise and producing superior segmentation quality. A hybrid K-means and DBSCAN for Photovoltaic module Hotspot Detection [54] uses K-means for image pre-processing followed by DBSCAN for final segmentation. DBSCAN is effective here because it identifies dense regions of high-temperature pixels as clusters, handles outliers, and identifies clusters of arbitrary shapes. A comparative study showed that integrating a Self-Organizing Network (SOM) with minimum distance and DBSCAN algorithms improves accuracy and reduces processing time compared to using the base algorithms alone [55]. A different approach [56] uses the SLIC (Simple Linear Iterative Clustering) algorithm to generate super pixels first, then applies the DBSCAN algorithm to an enhanced feature space that includes Lab colour values, compactness, and texture information for improved segmentation results.

Mumford-Shah model

Energy minimization in the context of image segmentation treats the task as an optimization problem where the goal is to partition an image in a way that minimizes an associated mathematical "energy functional." This functional is carefully designed to penalize undesirable segmentations (e.g., segmentations that cut through uniform regions or create noisy boundaries) and reward desired properties (e.g., smooth boundaries and uniform pixel values within segments). The Mumford-Shah model is a cornerstone of this approach, introduced in 1989 [19]. It seeks a segmentation that balances two competing goals: a) the segmented regions should closely approximate the intensity or colour values of the original pixels within them. b) the total length or complexity of the segmentation boundaries should be minimized to avoid an overly fragmented or "noisy" result [20]. This approach transforms the qualitative problem of "what looks like a good segmentation?" into a solvable mathematical equation.

The Mumford-Shah functional is defined as follows:

$$E(f, \tau) = \mu^2 \int_{\Omega} \|f - h\|^2 dx dy + \int_{\Omega - \tau} \|\nabla f\|^2 dx dy + \lambda L(\tau) \quad (1)$$

where function f approximates image h which is differentiable over the regions Ω_i :

$$\Omega = \bigcup_{i=1}^n \Omega_i \cup \tau$$

Here τ is the set of arcs forming the boundaries, μ and λ are positive weights that control the quality of the approximation and the coarseness of the segmentation, respectively, and $L(\tau)$ denote the total length of all the arcs belonging to τ . A large value of λ will lead to fewer boundaries. The goal is to minimize E , i.e., find f and τ so that E is minimized; the smaller the value of E , the better is the segmentation. The first term in equation (1) ensures that f approximates the image h , i.e., gives us homogeneous regions. The second term ensures that only smooth changes appear inside the segments. The third term prevents boundaries from growing very large. If the segments are homogeneous, the second term is no longer needed in Equation (2). We then obtain a simplified, piecewise constant Mumford-Shah model:

$$E(f, \tau) = \mu^2 \int_{\Omega} \|f - h\|^2 dx dy + \lambda L(\tau) \quad (2)$$

where λ is a parameter that controls the smoothness of the boundary.

The Mumford-Shah model and similar energy minimization models have seen extensive use across various image processing tasks, including image denoising, image segmentation, and image restoration [21]. Researchers utilize several advanced algorithmic techniques to minimize this complex functional, such as the Douglas-Rachford algorithm [22], and several implicit numerical methods [23]. While classic models like Mumford-Shah are highly effective and mathematically sound, modern deep learning has largely shifted the implementation paradigm. Instead of explicitly defining a mathematical energy functional to minimize with traditional optimization algorithms, modern neural

networks learn implicit energy functions or loss functions through training on vast datasets. These loss functions guide the network to produce segmentations that meet learned criteria for accuracy and quality. However, the fundamental concept of defining a target function to optimize—minimizing error or "energy"—remains central to all segmentation research.

III. COMBINED APPROACH

In image segmentation, the desired outcome is typically that pixels near each other in spatial Euclidean space are grouped into the same region, while pixels that are spatially distant are assigned to different segments despite the similarity in color characteristics. Hence, applying the standard k-means algorithm directly to pixel color values results in what is essentially pure color quantization. In this scenario, every pixel is classified based solely on its proximity to the nearest color centroid, completely ignoring its physical location within the image and how its neighboring pixels are mapped. This purely color-based approach often produces highly fragmented segments and is usually insufficient for effective image segmentation because the algorithm provides no control over the continuity, shapes, or convexity of the resulting regions. Spatial context must be explicitly added to the model to achieve meaningful segmentation.

On the other hand, other inherent challenges persist when applying clustering to images. Even when a simple spatial connectivity constraint is enforced, the resulting segments can still possess complex and convoluted shapes. Whereas adding spatial constraints typically encourages smaller, more localized segments, this very constraint can inadvertently hinder the algorithm's ability to identify and define segments of variable or large sizes. In ongoing research to bridge classical energy minimization techniques with efficient clustering algorithms, a significant development is the Mumford-Shah k-means (MS-KM) [19] algorithm and the Mumford-Shah Pairwise Nearest Neighbor [10].

Mumford-Shah k-means

In [19], a new variant called Mumford-Shah k-means (MS-KM) algorithm introduces the well-known Mumford-Shah model into the structure of the k-means algorithm. To incorporate the Mumford-Shah convexity criterion, a new term derived from the functional is used, specifically focusing on the total length of the segment boundaries. During the optimal partitioning process, the MS-KM algorithm makes assignment decisions that consider two factors simultaneously: the standard pixel intensity value and the pixel's effect on the overall boundary length, which is calculated directly from image gradients. In terms of efficiency the method maintains the computational speed of the classical k-means algorithm and is significantly faster than other complex optimization techniques typically used to solve the Mumford-Shah model in [23], [25], [26], [27], [28], [29]. Despite successfully employing the Mumford-Shah functional, the MS-KM algorithm inherits all the limitations of classical k-means. It functions primarily as a local fine-tuner and is prone to getting stuck in inferior local minima solutions.

Mumford-Shah Pairwise Nearest Neighbour

In [10], the most efficient PNN variant (k-NN) is adopted for image segmentation using the Mumford-Shah model. The key distinction from prior works is that the method is utilized not merely as a technique for vector quantization but is adapted to specifically incorporate the crucial element of the spatial connectivity of pixels, which is vital for meaningful image regions. The results obtained using the proposed MS-PNN [10] technique demonstrate superior performance compared to both regular K-means (reg-KM) [50] and the Mumford-Shah K-means (MS-KM) [24] techniques.



Fig. 2 Image from the work [10] comparing different hybrid methods

Combining DBSCAN and Mumford-Shah

Various approaches can be used to leverage the strengths of both DBSCAN and Mumford-Shah for image segmentation. One strategy could be to use DBSCAN for initial segmentation, identifying dense regions of pixels that are likely to belong to the same object or region. Subsequently, the Mumford-Shah algorithm could be applied to refine the boundaries of these initial segments, ensuring smooth and accurate edges while maintaining region homogeneity. This combined approach could potentially overcome some of the individual limitations of each method, leading to more robust and accurate image segmentation, particularly for images with complex shapes or noisy areas.

The challenge of selecting appropriate parameters for DBSCAN could potentially be addressed by using adaptive techniques, such as neural network-based approaches, to automatically determine these parameters based on image characteristics. Similarly, the computational complexity and potential sensitivity to initialization in Mumford-Shah could be tackled by combining it with faster algorithms like k-means or using optimized solvers like the Douglas-Rachford algorithm, according to research published in [22].

IV. CONCLUSION

Ultimately, the combination of these techniques could offer advantages in scenarios requiring segmentation of complex objects, noisy images, and situations where both region homogeneity and boundary accuracy are crucial factors in determining the segmentation quality. In summary, combining DBSCAN and the Mumford-Shah algorithm holds potential for robust image segmentation by blending density-based clustering with variational segmentation principles to handle both region homogeneity and boundary accuracy effectively.

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