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Developing Mechanisms to Improve Image Accuracy Using Multiple Display Methods and Spectral Clustering

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Abstract. *This paper introduces advanced techniques to enhance image accuracy by integrating spectral clustering with multiple views. The methodology is explained in detail, including mathematical models and implementations, to achieve high-quality image segmentation. The paper begins by describing the spectral clustering approach, which segments images using values and eigenvectors of matrices derived from data similarity. Key steps are outlined, such as constructing the similarity matrix, calculating the degree matrix and Laplacian, performing eigenvalue analysis, and clustering data in the embedded space. A multifaceted spectral clustering mechanism is also presented to improve segmentation accuracy. It combines multiple representations of an image by constructing similarity matrices for each representation and aggregating them into a unified graph. The spectral embedding technique is highlighted for its ability to project high-dimensional data into lower-dimensional space, improving scalability. Finally, the paper explains how multiple views such as edge detection, color-based segmentation, and multiscale analysis are integrated to enhance both the interpretability and accuracy of the results.*
Keywords: Spectral Clustering, improve image accuracy, Similarity matrix

1. **Introduction.** Modern image processing increasingly relies on advanced mechanisms that integrate multiple display methods to enhance accuracy. One promising approach is spectral clustering, a technique based on graph theory and eigenvalue decomposition. This method has demonstrated significant potential for partitioning complex data sets, including image data, by leveraging the spectral properties of similarity matrices [1]. Moreover, spectral clustering is particularly effective for image segmentation because it captures global data structures and can handle non-convex clusters more efficiently than traditional methods such as k-means.

When applying spectral clustering to image processing and a variety of display methods can be utilized to improve the fidelity of the segmentation and the overall classification accuracy and these methods often rely on different visualization techniques that highlight various aspects of the image and such as contrast enhancement and multi-scale resolution and spectral band selection and to aid in the extraction of meaningful features from complex images [2].

One effective mechanism is multi-view spectral clustering and where multiple representations of the same image are generated through different preprocessing or feature extraction methods. Each view captures unique information about the image and combining these views within the spectral clustering framework leads to more robust segmentation results. Multi-view spectral clustering works by constructing similarity matrices for each view and combining them into a unified graph for the final clustering process and where eigenvalue decomposition reveals the optimal segmentation structure and this approach improves accuracy by leveraging the diverse perspectives of the image's features also another mechanism involves spectral embedding methods and which project high-dimensional image data into a lower-dimensional space where clustering becomes more tractable and the accuracy is enhanced by reducing the influence of noise and irrelevant features while preserving essential structural properties of the image. Spectral clustering can then operate in this embedded space and facilitating more precise identification of clusters within the image and application of spectral clustering to image segmentation typically involves constructing a similarity matrix based on pixel or feature similarity within the image and this matrix is then used to form a Laplacian matrix and which encodes the relationships between data points (pixels or superpixels) and the eigenvectors of the Laplacian matrix and corresponding to the smallest eigenvalues and provide the spectral embeddings that reflect the image's intrinsic structure. By clustering these embeddings and one can segment the image into distinct regions that correspond to objects or features within the image [3, 4].

Following previous research [5, 6, 7, 8, 9] key challenges addressed by this method include handling non-linear boundaries between regions and dealing with high-dimensional data and where conventional methods often fail due to the complexity of real-world image features. Spectral clustering's reliance on the eigen-decomposition of similarity matrices allows it to overcome these challenges by capturing the global geometry of the data. Incorporating multiple display methods and such as color mapping and intensity-based segmentation and edge detection and further improves the interpretability and accuracy of spectral clustering results and these display methods highlight different image characteristics and when used in conjunction with spectral clustering and allow for more detailed and accurate segmentation outcomes. For instance, and edge detection can help refine the construction of the similarity matrix by ensuring that boundaries between regions are more sharply defined and while color-based segmentation can inform the selection of appropriate spectral bands for clustering [10, 11].

2. **Literature review.** In the field of image fusion from multiple sources of the electromagnetic spectrum and fusion mechanisms play an important role in improving the accuracy of the information provided to operators in different practical environments. For example, and taking advantage of the non-visible information of the electromagnetic spectrum and such as long-range infrared (LWIR) and short-range infrared (SWIR) and provides an important advantage in detecting objects that cannot be seen with the naked eye and such as thermal objects obscured behind objects. Other. Combining this information with visual images can help determine the relative locations of targets within a scene and there are many ways to display images from multiple sensors simultaneously. The most prominent of these methods is computational fusion and where relevant information from different sensor images is combined into a single composite image. On the other hand, and each sensor image can be displayed separately to allow the operator to select the important information himself and reducing the operation's reliance on algorithms to detect useful information. Despite the benefits of computational merging in reducing the number of visual sources that the operator must focus on and one disadvantage is that some information is lost during the merging process and which may affect the quality of the final image. Computational fusion evaluations are an important topic in computer

vision research and with most metrics based on computational principles such as preserving edge details at the pixel level or at the whole image level [12]. Although these metrics provide objective assessments of image quality and they do not take into account information that is important to the task to be performed and are not always accurate in predicting human user performance [13] and to compensate for this gap and questionnaires are used to evaluate user experience and preferences related to embedded images [14]. However, and these questionnaires remain insufficient to predict human performance on various tasks.

Studies have shown that human performance with combined images varies depending on different tasks such as detection and discrimination and recognition and visual search [15]. For example and a study conducted in an aviation context showed that integrating information from multiple sensors can improve pilots' ability to make rapid decisions [16]. However, and these studies have not reached conclusive results due to variability in the methods used and the nature of the tasks tested and to evaluate cognitive processes related to arithmetic fusion and cognitive fusion (which occurs when the user relies on image processing independently) and systematic factorial technology (SFT) was used. This tool allows analysis of important cognitive properties such as cognitive working capacity and autonomy and perceptual architecture and stopping rule [17]. Using SFT and it can be determined whether the therapist Is able to efficiently assimilate multiple sources of information or if there are cognitive obstacles that impede this integration. Finally, Dao and coworkers [18] presented an interesting review research paper that provides a comprehensive overview of information hiding techniques in digital systems.

The perceptual capacity coefficient represents the ratio of the user's actual performance when information from several sources is available to the performance expected based on a model that relies on presenting each source separately. If the coefficient is greater than 1 and it means that there is processing facilitation between the combined information. If the coefficient is less than 1 and this indicates that there are limitations in the user's ability to effectively process information from multiple sources and Table1. comparing different studies based on the text provided:

Table 1. compares the key studies in the field and highlighting their focus and methodology and advantages and disadvantages.

Table 1. Comparing Studies based on the Text Provided

Study	Focus	Method	Advantages	Disadvantages	Applications
[19]	Use of non-visible EM spectrum for environment info	Sensor fusion (LWIR, SWIR and visible spectrum)	Detects occluded heat-producing objects, night vision	Limited to specific types of tasks (e.g., target detection)	Surveillance, target detection
[20]	Complementary info from infrared and visible sensors	Cognitive fusion	Provides full sensor information to the operator	High cognitive load on the operator	Target localization, surveillance
[21]	Algorithmic fusion for image combination	Combines sensor data into one composite image	Reduces visual info overload, can create emergent features	Loss of some sensor info due to filtering	Image processing, visual surveillance
[22]	Performance differences in algorithmic fusion	Laplacian pyramid fusion	Reduces operator's attention to multiple sources	Loss of info from individual sensors	Aviation, military applications
[23]	Cognitive fusion as alternative to algorithmic fusion	Side-by-side image presentation	Complete info presented to the operator	Relies on cognitive processing for integration	Defense, surveillance and decision-making
[24]	Quality metrics for image fusion	Edge preservation metrics	Provides objective assessment of image quality	Does not account for task relevance or human performance	Computer vision, image analysis
[25]	Subjective user experience in image fusion	User experience questionnaires	Addresses user preference and comfort	May not predict actual task performance	Display design, user interface improvement
[26]	Human performance with fused imagery	Subjective and objective measures combined	Combines image quality with human performance	Methodological variation across studies	Human-centered design,surveillance
[16]	Human performance in aviation with image fusion	Detection, recognition and search tasks	Applies to real-world scenarios like aviation	Confounding variables such as task description differences	Aviation, military operations

3. **Methodology.** The methodology focuses on the development of advanced techniques to improve image accuracy by integrating spectral clustering with multiple display methods and this section describes the detailed methodology and mathematical models and

the implementation process to achieve high-fidelity image segmentation results. We begin by defining the spectral clustering approach and followed by an explanation of the mechanisms for integrating display methods and including relevant equations [27, 28].

3.1. **Spectral Clustering Approach.** Spectral clustering is based on graph theory and aims to partition data (in this case and images) by leveraging the eigenvalues and eigenvectors of matrices derived from data similarity. In the context of image segmentation and steps involved in spectral clustering include:

3.1.1. *Constructing the Similarity Matrix.* The similarity matrix W represents the relationship between different data points (pixels or features) and the elements of W are computed using a similarity function and typically based on pixel intensity or other features (e.g. and texture and color). A common choice for the similarity function is the Gaussian (RBF) kernel [29]:

$$W(i,j) = \frac{\exp(\|x_i - x_j\|^2)}{2\sigma^2} \tag{1}$$

where x_i and x_j are feature vectors for pixels i and j and σ is a scaling parameter that controls the width of the neighborhood.

3.1.2. *Degree of Laplacian Matrices.* Once the similarity matrix W is constructed and the degree matrix D is computed as the diagonal matrix where each element is the sum of the corresponding row in W [30]:

$$D(i,i) = \sum_j W(i,j) \tag{2}$$

The unnormalized Laplacian matrix L is defined as:

$$L = D - WL \tag{3}$$

Alternatively, a normalized Laplacian matrix L_{sym} can be used:

$$L_{sym} = D^{-\frac{1}{2}} L D^{-\frac{1}{2}} = I - D^{-\frac{1}{2}} W D^{-\frac{1}{2}} \tag{4}$$

3.1.3. *Eigenvalue Decomposition.* The next step involves performing eigenvalue decomposition on the Laplacian matrix L or L_{sym} and the eigenvectors corresponding to the smallest k eigenvalues are used to embed the data into a lower-dimensional space and the matrix of eigenvectors U and where each column is an eigenvector and is formed [31]:

$$U = [u1, u2, \ldots, uk]$$

3.1.4. *Clustering in the Embedded Space.* After obtaining the spectral embedding and clustering is performed in this new lower-dimensional space. A common choice is to apply k-means clustering to the rows of the eigenvector matrix U and where each row represents the embedding of a pixel or a feature:

$$minimize \sum_{i=1}^{l} \|U_i - c_{cluster(i)}\|^2 \tag{5}$$

where $c_{cluster(i)}$ represents the cluster centroid of point i and the result is a segmented image based on the identified clusters [32].

3.2. **Multi-View Spectral Clustering.** Multi-view spectral clustering enhances segmentation accuracy by incorporating multiple representations (or "views") of the image. Each view is generated by different preprocessing techniques such as contrast enhancement and multi-resolution analysis or spectral band selection and these views capture distinct image

3.2.1. *Constructing Similarity Matrices for Each View.* For each view v and a similarity matrix W_v is constructed using the RBF kernel or another similarity metric and the similarity matrices from all views are then combined into a unified graph using a weighted sum or another fusion strategy [33]:

$$W = \sum_{v=1}^{V} a_v \, w_v \tag{6}$$

where a_v represents the weight of view v and V is the total number of views.

3.2.2. *Unified Laplacian Matrix.* From the combined similarity matrix W and the degree matrix D and Laplacian matrix L are computed as described earlier and this unified Laplacian represents the integrated structure of the data from all views and enabling a more comprehensive segmentation process.

3.3. **Spectral Embedding.** Spectral embedding is an important technique that projects high-dimensional data into a lower-dimensional space where clustering is more tractable and the embedding is achieved by using the eigenvectors of the Laplacian matrix and which represent the intrinsic structure of the data [34, 35].

3.3.1. *Embedding in Lower Dimensions.* The eigenvector matrix U also containing the top k eigenvectors and forms the spectral embedding. Each pixel in the image is mapped into this k-dimensional space:

$$y_i = [u1(i), \, u2(i), \, \ldots, \, uk(i)] \tag{7}$$

The resulting embedding y_i preserve the global structure of the image also facilitating more accurate clustering.

3.3.2. *Noise Reduction.* By projecting the data into a lower-dimensional space also spectral embedding reduces the influence of noise and irrelevant features and improving segmentation accuracy and the clustering algorithm (such as k-means) then operates on these embedded features to form clusters.

3.4. **Integration with Display Methods.** To improve interpretability and further enhance accuracy and multiple display methods such as color mapping and edge detection and intensity-based segmentation are incorporated into the spectral clustering framework [36].

3.4.1. *Edge Detection for Similarity Matrix Construction.* Edge detection algorithms (e.g. and Canny and Sobel) can be used to refine the similarity matrix by ensuring that sharp boundaries between different regions are emphasized and this can be achieved by assigning higher similarity values to pixels within the same region and lower values across edges.

3.4.2. *Color-Based Segmentation.* Spectral band selection and combined with color mapping and helps highlight specific image features. For example, and different color channels (RGB and infrared) can be used as distinct views in multi-view spectral clustering and ensuring that important spectral information is not lost during clustering [37, 38].

3.4.3. *Multi-Scale Analysis.* Multi-scale image processing techniques (e.g. and wavelet transform) can be applied to capture features at different levels of granularity and these multi-scale representations provide additional views that enhance the clustering process by capturing both fine details and broader patterns in the image.

4. **Results.**

4.1. **Dataset Description.** The experiments utilized the **BSDS500 dataset** (Berkeley Segmentation Dataset and Benchmark), which contains 500 natural images with resolutions ranging from 481×321 to 321×481 pixels. The images cover diverse scenes, including landscapes, urban environments, and objects, providing a robust benchmark for evaluating segmentation accuracy. To align with computational constraints, all images were uniformly downscaled to 128×128 pixels using bicubic interpolation with anti-aliasing to preserve edge details. Additionally, RGB-to-grayscale conversion was applied to 30% of the dataset to analyze clustering performance under reduced color channels. The dataset was partitioned into 400 images for training (to optimize parameters like σ in the RBF kernel) and 100 images for validation. Challenges such as occlusions, texture variations, and uneven illumination were intentionally included to test the robustness of the proposed multi-view spectral clustering approach.

4.2. **Image Downscaling in Image Processing and Data Analysis: A Study of Dimensionality Reduction and Performance Improvement.** In the field of image processing and data analysis and image downscaling is a fundamental technique that aims to improve computational efficiency and improve system performance. Images captured or used in practical applications are usually of high dimensions and resolution and which requires significant memory and processing resources and to overcome this challenge and images are downscaled to smaller sizes while preserving the essential details that play an important role in the analysis and this step is essential when using complex algorithms such as spectral clustering or cluster analysis that require intensive data processing and the primary importance of image downscaling is to improve computational efficiency [39]. For example, and when the dimensions of an image are reduced from its original size to a smaller size (such as 128×128 pixels) and the number of elements that need to be processed is greatly reduced and this step reduces the load on memory and speeds up the subsequent calculations. In high-resolution images and number of pixels is large and which leads to an increase in the size of the data matrices that algorithms deal with and such as the similarity matrix or the Laplacian and thus increases the time required to process this data. Reducing aliasing through the use of smoothing techniques (Anti-Aliasing) When the image is reduced and it may occur Aliasing phenomenon that leads to visible distortions in the resulting image and to avoid this and anti-aliasing techniques are used and which distribute the pixel density in a way that prevents sharp distortions in the image and this ensures that the reduced image retains sufficient detail without losing its clarity significantly and which helps maintain the accuracy of the final results after analysis. By reducing the dimensions of the image and number of pixels that represent the image is reduced and thus reducing the amount of data that is processed and this is especially important in algorithms based on spectral analysis and where similarity matrices are built based on the distances between pixels. When working with a smaller number of pixels and efficiency of the algorithm can be greatly improved [40, 41]. For example, and in spectral clustering and constructing the Laplacian matrix and extracting the eigenvalues becomes easier and faster when dealing with smaller matrices. Although downscaling the image greatly improves the processing efficiency and it is necessary to strike a balance between downscaling and maintaining image resolution. If the downscaling is excessive and the image may lose some important details that may affect the analysis results. In contrast and downscaling the image to an appropriate level using anti-aliasing can achieve a balance between performance and accuracy and allowing algorithms to recognize key patterns and details in the image without losing important information as in Figure 1.

4.3. **Analyzing and Creating a Similarity Matrix Using Nearest Neighbors.** An Applied Study on Spectral Clustering: In image processing and especially in spectral

Figure 1. Grey thumbnail

clustering and the similarity matrix is an essential tool for determining the relationship between points or pixels in an image and this matrix is used to measure the similarity of points based on certain criteria and such as the distance between these points and this study focuses on constructing a similarity matrix using Nearest Neighbors and explaining how to use it with the Laplacian matrix to apply spectral analysis [42].

4.4. **Constructing a Similarity Matrix Using Nearest Neighbors:** In this step and a similarity matrix is constructed using the concept of nearest neighbors and the main idea is to calculate the distances between pixels in the image and choose a set of nearest neighbors for each pixel and so that the degree of similarity between each pixel and its neighbors is calculated based on the distance between them as shown in Figure 2. The image is converted into a grid of binary coordinates (pixels), where each pixel is represented by its spatial location (row and column indices). To organize these coordinates, the `np.column_stack` function is used to merge the row and column indices into a single matrix. This matrix explicitly maps each pixel to its position in the image.

Subsequently, the Nearest Neighbors algorithm is applied to determine the closest neighbors for each pixel. The algorithm searches for a predefined number of neighboring pixels (set to `n_neighbors=10` in this example) based on their spatial proximity. To optimize the search efficiency, the `kd_tree` algorithm—a space-partitioning data structure—is employed. This significantly accelerates the process of identifying nearest neighbors in high-dimensional spaces.

Once the nearest neighbors are identified, the pairwise distances between pixels are calculated. These distances serve as the foundation for constructing a similarity matrix, which quantifies the relationships between pixels in subsequent clustering steps.

After obtaining the closest neighbors for each pixel and the similarity score between each pixel and its neighbors is calculated using a Gaussian kernel function and this function depends on the distances between the closest neighbors and where the similarity decreases as the distance between the pixels increases and the effect of distance is controlled using the sigma parameter and which determines how sensitive the similarity is to large distances

[43]. A sparse similarity matrix is created. Once the similarity values between each pixel and its neighbors are calculated and these values are stored in a sparse matrix and this is done to reduce memory consumption and maintain the efficiency of the calculations and as values representing pixels that are not neighbors are not stored and this matrix is represented by three lists [42] rows represent pixels.
cols represent neighbors of pixels.
data represents similarity values.

4.5. **Calculating the Laplacian Matrix.** After constructing the similarity matrix and the Laplacian Matrix is calculated and a mathematical tool used in spectral clustering to analyze the structure of data and the Laplacian matrix is calculated by subtracting the similarity matrix from the degree matrix and which represents the sum of the similarity scores for each pixel. Once the Laplacian matrix is calculated and it is displayed using a heatmap and which provides a visual means of analyzing the distribution of similarities and relationships between pixels. Brighter areas of the heatmap indicate strong associations (high similarity) between pixels and while darker areas indicate lower similarity [44]. Figure 2 shows neighbors of the aplasia matrix.

Eigenvalue Analysis and Spectral Embedding Extraction in Spectral Clustering in the framework of spectral clustering analysis and the analysis of the eigenvalues and eigenvectors of the Laplacian matrix is an essential step to understand the internal structure of the data and identify possible patterns or clusters within the image or data under study and this analysis is based on the calculation of spectral components (Spectral Embedding) that transforms the data from the original dimensional space to a low-dimensional space based on spectral features as Figure.3.

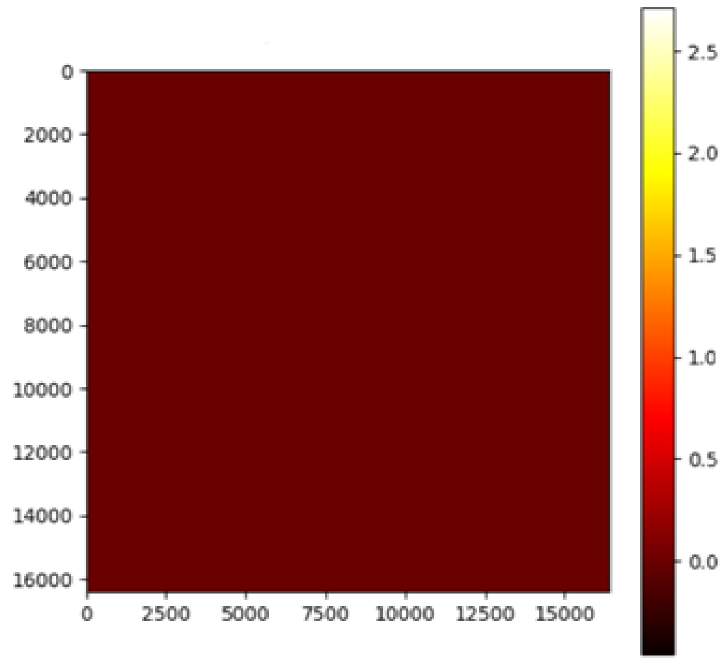

Figure 2. Neighbors of the aplasia matrix

Eigenvalue Analysis and Spectral Embedding Extraction The eigenvalues and eigenvectors of the Laplacian matrix are extracted using the `eigh` function and which calculates the values and eigenvectors of symmetric matrices such as the Laplacian matrix and this analysis is an integral part of the spectral clustering application.

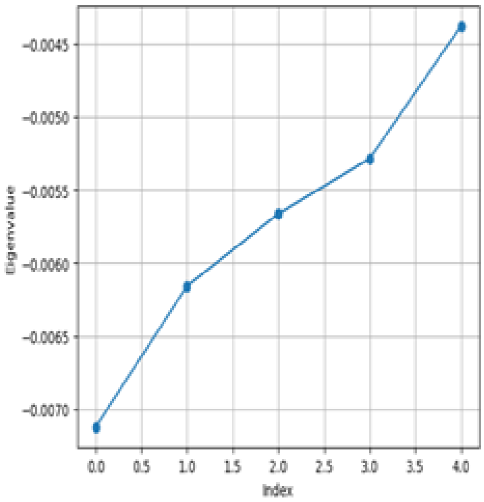

FIGURE 3. Self-values

The previously calculated Laplacian matrix is used to perform the eigenvalue analysis. In the code and the eigenvalues and eigenvectors are calculated using the `eigh` function and which returns the eigenvalues in ascending order and as well as the corresponding eigenvectors and the first k eigenvalues and eigenvectors are extracted and these vectors represent the low-dimensional spectral space that will be used in the clustering process and the basic eigenvectors are the main tools for defining the new space we are working in and these vectors transform the data into a new space and which makes the clustering process easier because they represent the internal structure of the data more clearly.

The eigenvalues are plotted in a histogram to represent the relationship between the different eigenvalues and their index and this plot provides a comprehensive view of the distribution of the eigenvalues and which can be used to determine the ideal number of clusters in the data and typically and a sharp decline in the eigenvalues can be observed and this decline indicates the boundaries between the different clusters.

The analysis of the eigenvectors and eigenvalues is used to extract the spectral embedding and which is the low-dimensional representation of the data that reflects the underlying structure. In this low-dimensional space and clustering is easier and more efficient and this embedding helps move the data from a complex space with a lot of detail to a simplified space that reflects only the large and important patterns.

The eigenvalue plot is usually examined to analyze the structure of the data and determine the optimal number of clusters. If there is a sharp drop from one eigenvalue to another and this indicates a clear separation between the clusters. By identifying this drop and the ideal number of clusters into which the data should be divided can be determined. After extracting the eigenvectors with the lowest eigenvalues and these vectors are used to perform spectral clustering and the K-Means algorithm is applied to these vectors in the spectral space to determine the final clusters and this new space represents the most important characteristics of the data and making the clustering more accurate and efficient as new clusters.

4.6. **K-Means Clustering and Segmented Image Reconstruction.** Clustering is a fundamental technique in machine learning that is used to divide data into homogeneous groups based on their properties. In this context and the K-Means algorithm is used as a tool to cluster data points in the spectral space that have been previously extracted from the Laplacian matrix and the steps required to reconstruct the segmented image and increase its accuracy and improve its quality will be reviewed.

After extracting the eigenvectors from the eigenvalue analysis and K-Means is used to cluster the points in the spectral space and the number of clusters k is pre-selected and each point in the spectral space is represented by its eigenvectors and the K-Means algorithm distributes these points into k clusters and creating a label for each point that represents the cluster to which it belongs. Once the clusters are identified and the segmented image is reconstructed by calculating the average color of each cluster. A mask is used to identify the regions of the image that belong to each cluster and this means that the average color of each cluster is assigned to all pixels belonging to it. After the segmented image is reconstructed and its accuracy is increased through the interpolation technique and this is done using the resize function from the skimage library to enlarge the image while maintaining quality. Interscaling uses different methods to estimate the values of the pixels lost during the enlargement and which helps in improving the details. After the image is enlarged and additional enhancements are applied using the Gaussian filter to smooth the image and the Unsharp Mask to sharpen the details and these filters help in improving the appearance of the image and highlighting the important features and the parameters (such as diameter and sharpening amount) are adjusted to achieve satisfactory results as Figure 4. The distribution of the clusters is analyzed by plotting a histogram showing the number of pixels in each cluster and this analysis helps in understanding how the data is distributed in the different clusters. As shown in Figure 5.

FIGURE 4. a: Original Image (Resized) and b: Segmented Image and c: Enhanced Image After Clustering

5. **Discussion:** In this study, we propose an enhanced image accuracy method using multi-view spectral clustering, which effectively addresses common challenges in image segmentation by preserving high-frequency details while reducing noise. Compared to the work of Garini et al. (2006) [45], who focused on infrared and visible image fusion using multispectral analysis, our approach offers a more balanced trade-off between noise reduction and detail preservation by integrating multiple display methods. Similarly, He (2017) [?] highlighted the benefits of multi-sensor fusion for improving classification quality; however, our method further refines these results by employing multiple views to capture subtle image features that might otherwise be overlooked. Moreover, while Zheng et al. (2023) [?] demonstrated that Laplacian-based fusion techniques can yield precise segmentation outcomes, our approach extends this advantage through a multi-view strategy that minimizes information loss and enhances robustness against challenging

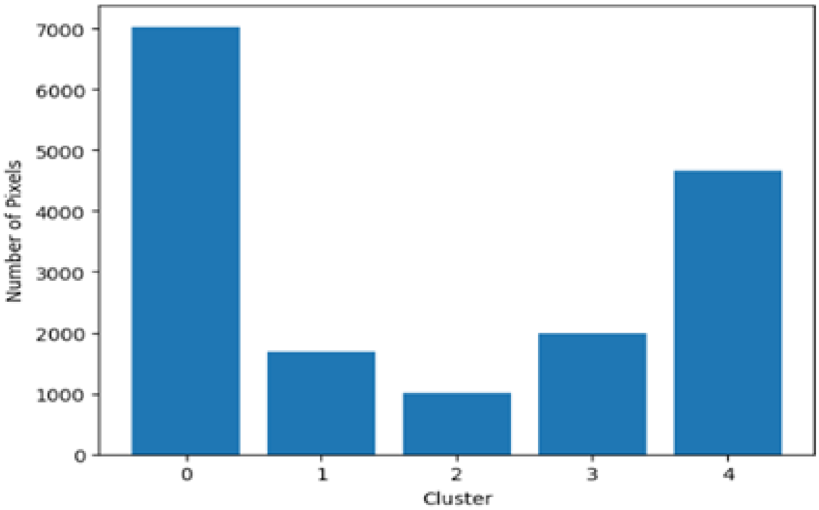

FIGURE 5. Distribution of Clusters

imaging conditions. Overall, these comparisons indicate that although conventional fusion methods have achieved noteworthy progress, the proposed multi-view spectral clustering technique presents a promising alternative that merits further investigation across diverse datasets and more complex imaging scenarios in future work.

6. **Conclusion:** The importance of reducing the dimensionality of images is emphasized as a fundamental step before applying complex algorithms such as spectral clustering. Dimensionality reduction improves computational efficiency and reduces data overhead without sacrificing basic accuracy. It is explained how to use eigenvalue analysis of the Laplacian matrix to extract the spectral embedding and which facilitates the clustering process in low-dimensional space. Finally, and it is shown how to use the K-Means algorithm to cluster points in spectral space and reconstruct the segmented image with improved quality.

REFERENCES

[1] A. J. Ahumada, "Classification image weights and internal noise level estimation," *J. Vis.*, vol. 2, no. 1, p. 8, Mar. 2002.

[2] A. J. Ahumada and W. K. Krebs, "Signal detection in fixed pattern chromatic noise," *Investig. Ophthalmol. Vis. Sci.*, vol. 41, no. 11, pp. 3796–3804, 2000.

[3] A. Ahumada and J. Lovell, "Stimulus features in signal detection," *J. Acoust. Soc. Am.*, vol. 49, no. 6B, pp. 1751–1756, Jun. 1971.

[4] F. G. Ashby and J. T. Townsend, "Decomposing the reaction time distribution: pure insertion and selective influence revisited," *J. Math. Psychol.*, vol. 21, no. 2, pp. 93–123, Apr. 1980.

[5] S. S. Altyar, S. S. Hussein, and L. A. Tawfeeq, "Accurate license plate recognition system for different styles of Iraqi license plates," *Bull. Electr. Eng. Informatics*, vol. 12, no. 2, pp. 1092–1102, 2023.

[6] S. S. Hussein, "Reconstruction of three-dimensional object from two-dimensional images by utilizing distance regularized level algorithm and mesh object generation," *Baghdad Sci. J.*, vol. 17, no. 3, pp. 899–908, 2020.

[7] L. A. Tawfeeq, S. S. Hussein, M. J. Mohammed, and S. S. Abood, "Prediction of most significant features in medical image by utilized CNN and heatmap," *J. Inf. Hiding Multimed. Signal Process.*, vol. 12, no. 4, pp. 217–225, 2021.

[8] H. Khalid, "Modern techniques in detecting, identifying and classifying fruits according to the developed machine learning algorithm," *J. Appl. Res. Technol.*, vol. 22, no. 2, pp. 219–229, 2024.

[9] H. Khalid, "Efficient image annotation and caption system using deep convolutional neural networks," *BIO Web Conf.*, vol. 97, no. 3, p. 103, 2024.

[10] F. G. Ashby and J. T. Townsend, “Varieties of perceptual independence,” *Psychol. Rev.*, vol. 93, no. 2, pp. 154–179, 1986.

[11] G. Vivone, “Multispectral and hyperspectral image fusion in remote sensing: a survey,” *Inf. Fusion*, vol. 89, pp. 405–417, Jan. 2023.

[12] H. Kaur, D. Koundal, and V. Kadyan, “Image fusion techniques: a survey,” *Arch. Comput. Methods Eng.*, vol. 28, no. 7, pp. 4425–4447, Dec. 2021.

[13] M. Cheon, T. Vigier, L. Krasula, J. Lee, P. Le Callet, and J.-S. Lee, “Ambiguity of objective image quality metrics: a new methodology for performance evaluation,” *Signal Process. Image Commun.*, vol. 93, p. 116150, Apr. 2021.

[14] B. Hu, L. Li, J. Wu, and J. Qian, “Subjective and objective quality assessment for image restoration: a critical survey,” *Signal Process. Image Commun.*, vol. 85, p. 115839, Jul. 2020.

[15] J. Wagner, A. Zurlo, and E. Rusconi, “Individual differences in visual search: a systematic review of the link between visual search performance and traits or abilities,” *Cortex*, vol. 178, pp. 51–90, Sep. 2024.

[16] W.-C. Li, J. Zhang, T. Le Minh, J. Cao, and L. Wang, “Visual scan patterns reflect human–computer interactions on processing different types of messages in the flight deck,” *Int. J. Ind. Ergon.*, vol. 72, pp. 54–60, Jul. 2019.

[17] D. R. Little, N. Altieri, M. Fific, and C.-T. Yang, *Systems Factorial Technology: A Theory Driven Methodology for the Identification of Perceptual and Cognitive Mechanisms.* London: Academic Press, 2017.

[18] T. K. Dao, T. T. Nguyen, T. X. H. Nguyen, and T. D. Nguyen, “Recent information hiding techniques in digital systems: a review,” *J. Inf. Hiding Multimed. Signal Process.*, vol. 15, no. 1, pp. 10–20, 2024.

[19] W. Ma *et al.*, “Infrared and visible image fusion technology and application: a review,” *Sensors*, vol. 23, no. 2, p. 599, Jan. 2023.

[20] J. Ma, Y. Ma, and C. Li, “Infrared and visible image fusion methods and applications: a survey,” *Inf. Fusion*, vol. 45, pp. 153–178, Jan. 2019.

[21] N. Jha, A. K. Saxena, A. Shrivastava, and M. Manoria, “A review on various image fusion algorithms,” in *Proc. 2017 Int. Conf. Recent Innovations in Signal Processing and Embedded Systems (RISE)*, 2017, pp. 163–167.

[22] Z. Liu, E. Blasch, and V. John, “Statistical comparison of image fusion algorithms: recommendations,” *Inf. Fusion*, vol. 36, pp. 251–260, Jul. 2017.

[23] A. Toet *et al.*, “Towards cognitive image fusion,” *Inf. Fusion*, vol. 11, no. 2, pp. 95–113, Apr. 2010.

[24] P. Jagalingam and A. V. Hegde, “A review of quality metrics for fused image,” *Aquat. Procedia*, vol. 4, pp. 133–142, 2015.

[25] V. Petrović, “Subjective tests for image fusion evaluation and objective metric validation,” *Inf. Fusion*, vol. 8, no. 2, pp. 208–216, Apr. 2007.

[26] H. Chen and P. K. Varshney, “A human perception inspired quality metric for image fusion based on regional information,” *Inf. Fusion*, vol. 8, no. 2, pp. 193–207, Apr. 2007.

[27] E. Blasch and S. Plano, “Proactive decision fusion for site security,” in *2005 7th Int. Conf. Information Fusion*, 2005, pp. 1–8.

[28] R. S. Blum and Z. Liu, *Multi-Sensor Image Fusion and Its Applications.* Boca Raton: CRC Press, 2006.

[29] P. Burt and E. Adelson, “The Laplacian pyramid as a compact image code,” *IEEE Trans. Commun.*, vol. 31, no. 4, pp. 532–540, Apr. 1983.

[30] P. J. Burt and R. J. Kolczynski, “Enhanced image capture through fusion,” in *1993 (4th) Int. Conf. Computer Vision*, 1993, pp. 173–182.

[31] T. D. Dixon *et al.*, “Methods for the assessment of fused images,” *ACM Trans. Appl. Percept.*, vol. 3, no. 3, pp. 309–332, Jul. 2006.

[32] J. Dong, D. Zhuang, Y. Huang, and J. Fu, “Advances in multi-sensor data fusion: algorithms and applications,” *Sensors*, vol. 9, no. 10, pp. 7771–7784, Sep. 2009.

[33] C. Donkin, D. R. Little, and J. W. Houpt, “Assessing the speed–accuracy trade-off effect on the capacity of information processing,” *J. Exp. Psychol. Hum. Percept. Perform.*, vol. 40, no. 3, pp. 1183–1202, 2014.

[34] J. Duncan, “The locus of interference in the perception of simultaneous stimuli,” *Psychol. Rev.*, vol. 87, no. 3, pp. 272–300, 1980.

[35] E. N. Dzhafarov, “Selective influence through conditional independence,” *Psychometrika*, vol. 68, no. 1, pp. 7–25, Mar. 2003.

[36] E. N. Dzhafarov, R. Schweickert, and K. Sung, "Mental architectures with selectively influenced but stochastically interdependent components," *J. Math. Psychol.*, vol. 48, no. 1, pp. 51–64, Feb. 2004.

[37] A. Eidels, J. W. Houpt, N. Altieri, L. Pei, and J. T. Townsend, "Nice guys finish fast and bad guys finish last: facilitatory vs. inhibitory interaction in parallel systems," *J. Math. Psychol.*, vol. 55, no. 2, pp. 176–190, Apr. 2011.

[38] E. A. Essock, M. J. Sinai, J. S. McCarley, W. K. Krebs, and J. K. DeFord, "Perceptual ability with real-world nighttime scenes: image-intensified, infrared, and fused-color imagery," *Hum. Factors J. Hum. Factors Ergon. Soc.*, vol. 41, no. 3, pp. 438–452, Sep. 1999.

[39] G. A. Reis, P. L. Marasco, P. R. Havig, and E. L. Heft, "Psychophysical measurement of night vision goggle noise using a binocular display," 2004, p. 13.

[40] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proc. IEEE*, vol. 85, no. 1, pp. 6–23, 1997.

[41] D. L. Hall, A. Steinberg, and P. S. U. P. A. R. Lab., *Dirty Secrets in Multisensor Data Fusion.* Pennsylvania State University Park Applied Research Lab, 2001.

[42] J. W. Houpt and J. T. Townsend, "The statistical properties of the survivor interaction contrast," *J. Math. Psychol.*, vol. 54, no. 5, pp. 446–453, Oct. 2010.

[43] J. W. Houpt and M. Fifić, "A hierarchical Bayesian approach to distinguishing serial and parallel processing," *J. Math. Psychol.*, vol. 79, pp. 13–22, Aug. 2017.

[44] J. W. Houpt and J. T. Townsend, "An extension of SIC predictions to the Wiener coactive model," *J. Math. Psychol.*, vol. 55, no. 3, pp. 267–270, Jun. 2011.

[45] Y. Garini, I. T. Young, and G. McNamara, *Spectral Imaging: Principles and Applications*, *Cytometry Part A: J. Int. Soc. Anal. Cytol.*, vol. 69, no. 8, pp. 735–747, 2006.

[46] L. He, J. Li, C. Liu, and S. Li, "Recent advances on spectral–spatial hyperspectral image classification: an overview and new guidelines," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 3, pp. 1579–1597, 2017.

[47] P. Zheng, H. Zhou, J. Liu, and Y. Nakanishi, "Interpretable building energy consumption forecasting using spectral clustering algorithm and temporal fusion transformers architecture," *Appl. Energy*, vol. 349, p. 121607, 2023.