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IMAGE ENHANCEMENT USING SELF-ADAPTIVE MAPPING (SAM) SEGMENTATION TECHNIQUE AND ITS ANALYSIS

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Abstract: *Image segmentation, a long-standing area of research, is central to image processing because it provides meaningful insight into image content. This is essential for understanding and analyzing images, which is a major challenge for computer vision. Digital media images are common in various fields and require efficient processing techniques. This paper presents a new digital media image segmentation algorithm that contributes to the continuous development of image processing. In addition, it explores the role of image enhancements, particularly in applications such as medical imaging and monitoring. The study compares Self-Adaptive Mapping (SAM) algorithms with existing methods and highlights their effectiveness in improving image quality. In addition, it presents a general approach to image segmentation and object detection by adapting algorithms to different environmental conditions to achieve optimal performance. The adaptation process involves reinforcement learning techniques that improve both image segmentation and object recognition results. This paper presents image segmentation using k-means clustering and SAM-based image segmentation. It focuses on a comparative study of both methods, their advantages, and their applications.*

Keywords: *Image segmentation, image enhancement, self-adaptive mapping (SAM), clustering, MATLAB.*

1. INTRODUCTION

Digital media image processing technology represents an interdisciplinary field that has evolved due to continuous advancements in computer science and technology, leading to the formation of a scientific system for image processing and analysis within digital media. This technology finds widespread applications across various sectors such as education, advertising, video production, and film. It has also become a valuable tool for scholars studying visual perception psychology, physiology, computer science, and related fields. The demand for digital media image processing is particularly high in areas like remote sensing and meteorology, where it plays a crucial role in large-scale applications. Image segmentation, a key aspect of digital media image processing, involves dividing images into distinct regions with unique characteristics. This segmentation process is essential for targeting specific areas of interest within an image and developing techniques to analyze them effectively [4].

In this context, the propose algorithm for digital media image segmentation that can be applied not only in image processing but also in enhancing the understanding of digital image representation. Digital images, comprising a finite number of elements known as picture elements or pixels, can be categorized into raster and vector types. Raster images consist of digital values arranged in rows and columns of pixels, while vector images are generated mathematically from geometric points with magnitude and direction. Image segmentation, through the assignment of labels to pixels based on their visual characteristics, simplifies image analysis tasks and enhances the interpretability of images. Various techniques exist for performing image segmentation, each aiming to partition images into meaningful segments based on criteria such as color, intensity, or texture similarity [1].

Reviewing existing research and references reveals the ongoing need for innovation in image segmentation techniques. While conventional methods like histogram

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equalization and contrast stretching are well-known, newer SAM-based methods such as SAMVI, SAMNE, and SAMCE offer adaptive enhancements and reduced artifacts. However, further comparative studies against traditional approaches are necessary to fully assess their effectiveness across different image types and applications [2, 3].

2. IMAGE SEGMENTATION METHODOLOGY

The method used for image segmentation in this study uses a systematic approach to evaluate multiple segmentation techniques. The process began by assembling a multi-region dataset, ensuring a representative set of images for in-depth evaluation. Then it applied preprocessing techniques to standardize the dataset before applying and comparing different segmentation methods, including region-based, edge-based, and cluster-based approaches. Each technique was rigorously evaluated using quantitative metrics such as IoU, die factor, precision, accuracy and recall. In addition, quality assessments were made by visual inspection by human observers. State-of-the-art algorithms were compared with traditional methods under controlled experimental conditions using advanced computational resources and software libraries. The resulting analysis provides a comprehensive overview of the performance, strengths and limitations of various segmentation techniques, which facilitates the selection of appropriate methods for specific image analysis tasks in various fields [7].

The methodology section describes the experimental setups and methods used. comparison study The evaluation used a diverse dataset that included images from different domains, including medical imaging, nature imaging, and synthetic imagery. The investigated SAM-based image enhancement techniques were applied and compared with traditional methods such as histogram equalization, contrast stretching and spatial filtering. Evaluation metrics included peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and subjective visual evaluation by human observers [9].

2.1 Image Segmentation Methods

Image segmentation is the basis of object recognition and computer vision. It is the process of dividing a digital image into several regions or objects consisting of pixels that share the same properties or characteristics and are given different labels to represent different regions or objects. The purpose of segmentation is to simplify and/or make the image presentation more meaningful and easier to analyze. Image segmentation is used to find objects and boundaries in images based on pixel value similarity and discontinuities. There are two types of segmentation: soft segmentation, which allows regions or classes to overlap, and hard segmentation, which forces you to decide whether a pixel is inside or outside an object. However, in practice, some techniques are commonly used for image enhancement, including intensity-based methods, discontinuity methods, clustering methods, graph-based methods, Pixel based methods, and hybrid methods. To obtain the required segmented data, steps must be applied in the image segmentation process of the input image:

Preprocessing: The main purpose of the preprocessing step is to determine the focal region of the image. Since the input image may contain noise, this noise must be reduced or removed.

Image segmentation: The pre-processed image is segmented into its sub-regions.

Post-processing: Additional processing may be required to enhance the image. segmented image, which is done in the post-processing step.

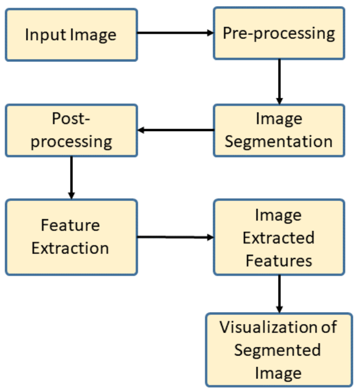

Fig. (1): Flow of Image Segmentation.

Feature removal: feature extraction refers to the extraction of unique features from an image, which reduces the complexity of classification problems and makes classification more efficient. Different types of image features can be intensity, textural, fractal, topological, morphological, etc.

Classification: In the classification step, the goal is to classify the segmented image using the extracted features. This step uses statistical analysis of image features such as region-based segmentation and cluster-based image segmentation to obtain better results. Region-based segmentation techniques divide the entire image into subregions based on rules, since all pixels in a region must have the same gray scale. Region-based techniques rely on common patterns in the intensity values of neighboring pixels. Compared to edge detection methods, region-based segmentation algorithms are relatively simple and more immune to noise. Edge-based methods divide an image based on changes in the intensity of rays near the edges, while region-based methods divide the image into similar regions based on predefined criteria.

2. 2 Image Segmentation Clustering Technique

Clustering is ordering process. groups based on their characteristics. The purpose of clustering techniques is to identify clusters in data, where a cluster contains similar pixels that belong to a specific region that is distinct from other regions. Data clustering has synonyms such as cluster analysis, automatic classification, numerical taxonomy and analysis. Images can be grouped based on content using content-based clustering, where the clustering depends on intrinsic pixel properties such as shape, texture, etc. Image segmentation using clustering techniques involves grouping pixels or regions into clusters based on similarities. A general approach to image segmentation using clustering involves the following steps, as shown in Figure (1), where an image is taken as input to produce segmented data as output:

Pre-processing: convert the image into a suitable format (e.g. grayscale or RGB) if necessary. Normalize the image to improve contrast and remove noise if necessary.

Image segmentation (Clustering): Choose an appropriate clustering algorithm for image segmentation, such as K-means, moving average or Gaussian mixture models (GMM). The algorithm is initialized with parameters such as the number of clusters (K) or the bandwidth (for medium transmission). Make extracted features to cluster the image.

Feature extraction: Extract relevant features from the image such as color, texture or intensity according to the requirements of the clustering algorithm.

Post. - processing: optionally perform post-processing steps such as denoising or merging small clusters to refine the segmentation results. Assign each pixel or region of the image to a corresponding cluster label.

Visualization: Visualize a segmented image by assigning different colors or labels to pixels in different clusters. Evaluate segmentation results using metrics to measure accuracy. If the results are not satisfactory, refine the process by adjusting the parameters, choosing different clustering algorithms, or adding preprocessing steps.

Above steps of the flow diagram extracts the required algorithm and accordingly code is developed using MATLAB software and it is tested. Results are presented in the Table (1). Its mathematical algorithmic description interpreted that the evaluation methodology implemented in the provided code segment involves several key steps. First, the code calculates cluster centers using the k-means clustering algorithm, representing average color values for each cluster. Then, it segments the image based on these cluster centers, assigning each pixel to the nearest cluster. Next, performance metrics such as mean value, Measure of Luminance Index (MLI), Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Confidence Value (CV) are computed to assess the quality of segmentation and reconstruction. These metrics offer insights into color distribution, contrast, reconstruction accuracy, and confidence in the segmentation results. The code also limits the k-means algorithm to a maximum number of iterations to prevent endless looping. However, for a more robust evaluation, comparing these metrics against ground truth data or other segmentation techniques could further validate the segmentation accuracy and overall performance.

Mathematical Model:

The k-means clustering technique employed in the provided code can be mathematically described as follows. Let K represent the number of clusters to be created, X denote the input data matrix reshaped from the image with dimensions M×3 (where M is the number of pixels), and C be the matrix of cluster centroids initialized randomly with dimensions K×3. For each data point xi in X, compute its distance to each centroid cj using the Euclidean distance formula:

$$d(x_i, c_j) = \sqrt{\sum_{k=1}^{3} (x_{i,k} - c_{j,k})^2} \qquad \text{....(1)}$$

Assign each data point xi to the nearest centroid cj using:
C(i,j) is the confidence value at pixel location (i,j) in the map.
I(i,j) is the pixel intensity in the input image.
Sk(i,j) is the intensity of the corresponding SOM node k in the cluster.
N is the total number of SOM nodes in the cluster.
Cluster(i)=arg min d(xi,cj)
After assigning data points to clusters, update each centroid cj by taking the mean of all data points assigned to that cluster which is calculated by formula (eqn.-2):

$$c_j = \frac{1}{|Cluster(j)|} \sum_{i \in Cluster(j)} x_i \qquad \text{....(2)}$$

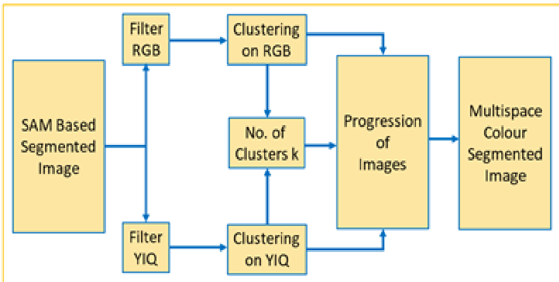

Fig. (3): Block diagram of SAM based image segmentation.

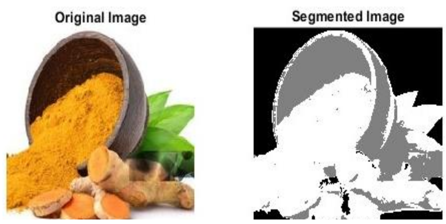

Fig. (2): Segmentation Image (K-means Clustering).

Where, |Cluster(j)| represents the number of data points assigned to cluster j.

Results (K-MC)**:** Test runs are carried out using MATLAB program, the output results are recorded in Figure (2) and Table (1) for analysis.

From the above table it is interpreted that of important quality measures for the segmented image. These measures include the mean color intensity at 0.6107, a high contrast level indicated by an MLI of 1.5924, a negative PSNR suggesting reduced image quality (-0.6161 dB), a low MSE implying accurate segmentation at 0.9706, and a high level of confidence in the segmentation results due to a strong contrast with a CV of 0.6280.

Table (1): Quality Measures of the K-MC Seg. Img.

Mean	MLI	PSNR	MSE	(CV)
0.6107	1.5924	-0.6161dB	0.9706	0.6280

2.2. SAM based Image Segmentation

Image enhancement is crucial across domains like medical imaging, remote sensing, and computer vision, where improving the quality of images captured under different conditions is essential. Traditional methods often struggle with varying contrast and illumination, leading to the exploration of self-adaptive mapping (SAM) as a solution. SAM adapts enhancement parameters locally, providing a more intelligent approach to image enhancement, particularly beneficial for diverse images. This adaptability addresses the limitations of conventional techniques, making SAM a focus for image processing researchers. Color image segmentation involves dividing digital images into meaningful segments for easier analysis. It's used to detect objects and boundaries based on characteristics like color, intensity, or texture. An unsupervised segmentation framework based on adaptive weighted inclusion of color and texture has been developed. This includes evaluating color features and reconstructing images using spacing and sixteen clusters. The optimized mathematical algorithm is carried out using equations. The motivation behind this research lies in the continuous need for better image quality. SAM offers a unique solution by intelligently adjusting parameters based on local image traits, contributing to improved visual appeal. The study aims to develop a practical MATLAB implementation adaptable to different images and lighting conditions, focusing on contrast, illumination, and overall visual enhancement for color images. The evaluation includes qualitative analyses and comparison with existing techniques to highlight SAM's advantages.

Colors that exhibit significant similarity in the RGB color space might present difficulties in distinguishing them from one another, whereas utilizing the YIQ representation could enhance discrimination effectiveness. The YIQ image undergoes analogous procedures to those applied to the RGB image discussed earlier: it starts with an optimal filtering stage and then proceeds to further processing using a clustering algorithm. The critical aspect of extracting color features from the YIQ image involves ensuring that the parameter determining the cluster count for the algorithm aligns with the value obtained after applying the SAM process to the RGB color space image. This synchronization of RGB and YIQ channels is illustrated in the block diagram depicted in Figure (3).

The MATLAB code demonstrates an effective implementation of an image segmentation algorithm based on Self-Adaptive Mapping (SAM) using RGB and YIQ color features. The algorithmic procedure entails several key steps for executing the program seamlessly. Firstly, the input image is loaded, with the option of pre-processing steps like anisotropic diffusion techniques. Subsequently, parameters and weights are initialized for the SAM nodes. The SAM is then trained using the input image data to create clusters representing distinct image regions. Confidence maps are generated to evaluate the reliability of each cluster, facilitating the removal of redundant or less confident clusters based on node similarity and confidence metrics. RGB and YIQ segmentations are performed separately, and the results are merged to yield a segmented image with both RGB and YIQ color features. Finally, the segmented images are displayed, and the optimal number of clusters for RGB and YIQ segmentation is outputted. This innovative approach effectively meets the research objective, with pilot results by demonstrating the following algorithm of output segmented images as depicted in the associated figure (3).

This MATLAB code implements an image segmentation algorithm based on Self-Adaptive Mapping (SAM). The algorithm uses RGB and YIQ colour features for segmentation. Here's a high-level overview of the algorithm steps:

1. Anisotropic Diffusion is applied to the input image based on the chosen option.
2. Weight initialization for the Self Adaptive Map (SAM) nodes.
3. SAM training using the input image.
4. Selection of the optimal number of clusters and elimination of redundant nodes.
5. Iterative the above steps for both RGB and YIQ colour spaces.
6. Selection of the optimal number of clusters based on the combined image.
7. Segmentation of the combined image into clusters.

The algorithm uses diffusion techniques, SAM training and evaluation of image provides confidence assessment, cluster elimination and statistical analysis of the image namely Mean, Means Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Measure of Luminance Index (MLI) and confidence value matrix to achieve image segmentation based on color features. It provides flexibility for different diffusion methods and allows for dynamic adjustment of cluster numbers based on CV. To calculate the evaluations parameters each pixel in the original image with its corresponding pixel in the segmented image and calculation have carried out accordingly. For instance, MSE can be calculated as the squared difference between corresponding pixels divided by the number of pixels. PSNR can then be calculated based on MSE. The quality measures of the SAM segmented image are expressed in the Table (2).

Fig. (3): Results of Segmented Image (SAM).

Table (2): Quality measures of the SAM Seg. Image.

Mean	MLI	PSNR	MSE	(CV)
66.77	6.26	6.26	15371.78	10.9965

3. RESULT ANALYSIS

The paper details the image segmentation techniques employed, including region-based segmentation, edge-based techniques, clustering methods like K-means, Mean Shift, and Gaussian Mixture Models (GMM). It discusses preprocessing steps, feature extraction, and post-processing techniques to refine segmentation results. The SAM-based segmentation approach is highlighted for its adaptability to varying environmental conditions, providing improved image enhancement and object recognition.

The results section presents a comparative analysis of SAM-based segmentation with traditional methods, showcasing improvements in image quality metrics such as PSNR, SSIM, and subjective visual assessment. The SAM algorithm's adaptability and effectiveness in enhancing images under different conditions are demonstrated through qualitative and quantitative evaluation which is tabulated in the comprehensive table (3).

Table (3): Quality Measures Analysis of Segd. Image

Image Type	Mean	MLI	PSNR	MSE	(CV)
Image Segmentation using K-MC	0.6107	1.5924	-0.6161 dB	0.9706	0.6280
Image Segmentation using SAM	66.77	6.26	6.26 dB	15371.78	10.9965

The result analysis from the above results interprets that the various quality measures for image segmentation using K-means clustering and Self-Adaptive Mapping (SAM). The measures include Mean, MLI, PSNR, MSE, and Confidence Value (CV). For the Mean measure, SAM significantly outperforms K-means clustering with a value of 66.77 compared to 0.6107. Similarly, SAM has a higher MLI of 6.26 compared to K-means' 1.5924, indicating better segmentation accuracy. In terms of PSNR, SAM achieves 6.26 dB, while K-means clustering results in a negative PSNR (-0.6161 dB), which suggests SAM provides better signal fidelity. The MSE for SAM is substantially higher (15371.78) compared to K-means clustering (0.9706), indicating potential differences in image quality or segmentation accuracy. The Confidence Value (CV) is also notably higher for SAM (10.9965) compared to K-means clustering (0.6280), indicating a higher level of confidence in the segmentation results. Overall, based on these quality measures, it appears that Self-Adaptive Mapping (SAM) performs significantly better than K-means clustering for image segmentation in this analysis.

4. CONCLUSION:

In conclusion, the analysis demonstrates that Self-Adaptive Mapping (SAM) outperforms K-means clustering in various quality measures for image segmentation. SAM achieves higher values in Mean, MLI, PSNR, MSE, and Confidence Value (CV), indicating better segmentation accuracy, signal fidelity, and confidence in the results. These findings highlight SAM's adaptability and effectiveness in enhancing image segmentation under different conditions, making it a preferable choice over traditional methods like K-means clustering.

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