An Ensemble of K-Means with Median Filter for Segmented Image

Pankaj Malik
Computer Science,
Pacific University,
Ujjain, India.

Dr.Jitendra Shitlani
Computer Science
Ujjain, India.

Abstract— **Image segmentation indeed a method of collecting data from a Image using numerous available algorithms and methodologies. Object segmentation is a significant & difficult role in the field of picture review & various Machine View, Image detection, scene perception & methods of object recognition. In this research paper, we will establish a color-based segmentation approach using median filter k-means that will help to segment and evaluate fruit shapes with an enhanced segmented image. The suggested approach relies on hybridizing fuzzy c-means as well as a median filter into algorithm k-means. Fruit dependent on segmentation conducted on fruit pictures. Therefore, the approach suggested may have implementations in various areas such as predictive sorting, overlapping fruit identification and extraction of an information ripeness of fruit.**

***Keywords*— Image processing, Image Segmentation, Otsu's method Clustering, Fuzzy c means, k-means, Median filter.**

I. INTRODUCTION

Image Segmentation is an important step in processing images and also an essential computer vision area. Segmentation of images is the method of separating relevant features or Image Regions. Such attributes may the first one features of image, including the gray color of a pixel, color, reflective Characteristics & structure etc. The spatial spectrum may also be, including elements of the histogram. The aim optimization of the image separates representation in num of categories that are not intersecting and can render the regions coherent & the characteristics of the neighboring regions clearly differ. Segmentation of images is among the most popular significant issues in machine vision science. It has now become a hotspot in the world of imagery [1][2]. Recently, Wong [3] proposed the method of local phase-coherent based on a human perceptual system which is used to determine the suitable bilateral filter parameters for the pixel of interest, but its computation is highly complex. The slope restoration technique [4] has been used to increase the edge sharpness, particularly, by adding the offset function to range filter of bilateral filter. In [5], the Gaussian gradient technique is used to identify whether the sequence of interesting pixels is flat or edge component. Then, the optimized bilateral filter parameters for each pixel are chosen based on the derived gradient

A. Preprocessing in Image Segmentation

The grouping pixels with similar characteristics is the method of segmentation of the image into several classes (sets, segments). The reference functions and the resemblance measures used vary depending on the method. Natural image segmentation requires the segments collected relate to the human intuitive understanding of segments. The conclusion we created is this is item or piece of goods in the scene is usually built only single substance & is therefore homogenous in color. High differences in color would, therefore, mean limits b/w all objects. So several segments; will mean several artifacts & elements of substances [6].

B. Image Smoothing

Until optimization, for eg, it will be to smooth the image and give - pixel approximate value of that same pixel of its neighborhood. This could results in uniform areas with smaller differences of color than that of the main image that would maximize optimization in terms of producing more adjacent sections. Some information will be lost, however, borders would be distorted as well as the proper boundaries for the area would be unidentifiable. Often this approach will lead to groups only blurry edge pixels under a picture section. Good smoothing outcomes will be achieved if we could evaluate the pixel neighborhood locally and use only those pixels identical with and equivalent to the main pixel [.7].

In this remaining paper, we 1stprovide some related work in section II. Section III gives a proposed model for getting an improved segmented image and Experimental analysis is presented in Section IV. The paper is concluded in Sections V.

II. RELATED WORK

W. Wang et al. [2019] Presented an analysis for high-noise distorted hyperspectral images, BF-MD-LBF configuration a being proposed. There will be two important steps in a proposed method: (1) KPCA applied to the (LBF) Local binary fitting method for resources and a new design for energy use developed take advantage of spectral information; (2) The bilateral filters is incorporated as a regularization concept in the LBF energy feature to construct a hyperspectral picture smoothed without blurring the edges. Such strategies can achieve greater optimization results once an oil spill picture is clear but doesn't accurately segment the oil spill region if the photo is blurred by high volume as well as the oil spill field [8].

Z. Chen et al. [2019] Suggested a BF approach based on the superpixels, Super BF. This algorithm divides an HSI by means of superpixel segmentation then filters into many homogeneous areas homogeneous section separately by BF; This method ensures that even the pixel structure of the prototype during BF is identical to this during the filters process, decreases chances of creating mixed pixels to increase the efficiency of the image array. SVM classifier for classifying the relevant Super BF features shall be used to check the feasibility of this proposed method. Studies of 3 widely used HSI datasets have shown that Super BF exceeds both the conventional hyper-spectral extraction method based on BF and some new extraction techniques [9].

Y. Zhang et al. [2019] A innovative longitudinally directed super-resolution (SR) technique have been developed of Neonatal Pictures. It's inspired according to the reality that after birth the brain grows anatomical constructs change slowly and smoothly. They suggest a technique involving longitudinal regularization in conjunction with low-rank and absolute variance restrictions, analogous to bilateral filtering, To resolve the inaccurate inverse issue related to the SR image. Experimental evidence on neonatal MR pictures shows that the suggested technique restores precise structural information and exceeds state-of-the-art approaches, both objectively and empirically, while Neonatal magnetic resonance (MR) pictures are typical of low spatial resolution & insufficient tissue contrast. Techniques of interpolation are widely applied to upsample that pictures for study afterward. The resulting images, however, are sometimes distorted and vulnerable to partial volume impact [10].

P. Zhang and L. Kong [2018] It article suggest an upgraded methodology for Otsu. Firstly, a bilateral filter screens the gray image and then measures the threshold to the optimum weighted interclass and intra-class ratio as the optimal optimization limit for defects. Results of simulation show that even a better Otsu algorithm will be found as well as the pre-processing effect will be because the defects on the surface of rail wheels will substantially reduce wheel performance and quality. Therefore it is of great importance to accurate segmentation of factory defects before actual bent spokes. To find any faults in the wheel correctly [11].

Q. Hou and C. Jung [2017] Proposed effective Depth of Light field estimate of the occlusion using bilateral filtration driven by segmentation. First, we use optical refocusing to measure the refocused views from either the field of view. Third, we conduct a classification of SVM to distinguish occluded pixels and non-occluded pixels. Second, we do multiple cost estimates on occluded & non-occluded pixels, & eliminate noise by filtering cost range. Eventually, we conduct bilateral filtering driven by segmentation to optimize the depth map while maintaining edges. Experimental results on both synthetic as well as our own data sources demonstrate which proposed method performs reliable occlusion light field depth estimation while retaining edges successfully. [12].

J. Wang et al.**[2017]** implemented an effective imaging demonstration approach using a bilateral filter and dimensional separation, taking into account both spatial proximity & distance amid interpolated pixel & the adjacent pixels. The spatial similarity is known as a locality of space. We use an adaptive weighted average to approximate the missing pixel value, measuring the adaptive weight based on three components: directional separation, the correlation between the pixel and each one of its neighboring pixels, and spatial position. The findings of the experiment indicate that the strategy suggested outperforms current methods in both objective and subjective efficiency [13].

A. K. Gautam and M. R. Bhutiyani [2016] Suggested a new approach by recombining major component transformed images (PCTs) and bilateral filtering dependent fused images to facilitate unsupervised segmentation of the hyperspectral signal. For simulation improvement and segmentation PCT and a bilinear filtering-based method were applied. The very first three PCT images comprise over 95 percent of the resources as well as the lowest output variance. The bilinear filter maintains sharp edges, & smoothens image. The composite picture will benefit from both approaches and provide improved segmentation outcomes. Experiments were carried out on a hyperspectral representation of HYDICE. For comparison, various segmentation metrics, such as Sensitivity, Precision, False Positive Rate (FPR), Accuracy & Matthews Correlation Coefficient (MCC), contrasted segmentation effects of strategies in contradiction of ground truth dataset. The suggested methodology gives better efficiency than other approaches and the comparative findings have also proven that [14].

III. Proposed Methodology

a) Problem Definition

The fragmenting of photographs does not produce desirable results in contrasting pictures taken outdoors with original images because of their absence on the surface of the film ... The composition of objects is influenced differently by different forms of lighting.

b) Proposed Work

First, we search the picture i.e. RGB to HSV translation and then apply the otshu threshold with fuzzy c-means on it and then apply k means clustering using median filter.details as continues to follow:

a) Conversion of RGB to HSV

An RGB color scheme is also an integrated lighting process in which, green, red & blue light is blended to each other in replicate a wide color of range in different ways. A brand name derives from the names of three main additive shades, green, red, & blue. HSV–(hue, saturation, value), also identified as HSB (hue, saturation, brightness), is used by many artists since Through hue or saturation, it is often much more reasonable than in additive or subtractive color elements to think of a color. HSV is a transition from color to RGB color space, as well as its components and colors, which are connected to the RGB color space it comes from. We first translate RGB to HSV format. For instance: HSV= rgb2hsv(RGB) transforms the RGB image's red, green & blue values to the HSV image's hue, saturation and color (HSV) values. [15].

b) Image Binarization using Otsu Thresholding

Simply, it is an image thresholding algorithm for the reduction of a gray level image to a binary image. A threshold is chosen to reduce the intraclass difference in black and white index pixels. The Otsu approach for binarization in image processing is an efficient thresholding way. The ideal threshold value of the input image can be determined by running through all possible threshold values (from 0 to 255). This thresholding algorithm has been investigated and proposed to define the optimal threshold value. In this experimental study, the Otsu thresholding algorithm is tested with several images [16].

c) Fuzzy C-means

Dunn[17] first implemented the clustering algorithm Fuzzy C-Means (FCM), and Bezdek[18] later extended it. The thing is industrialized by changing the FCM algorithm's standard accurate function with such a penalty term that takes the effect of neighboring pixels on the center pixels into account. The algo is an iterative clustering method which creates an optimal c partition by minimizing the weighted error target of the group's sum

$J_{FCM.}$

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik}{}^{q})\, d^2(x_k v_i) \qquad (1)$$

where X = {x_1, x_2, · · ·, x_n} ⊆ Rp is The set of data in p- Sided vector space, n is really the set of data components, c is no. of clusters with 2<c < n, uik is the membership degree of xk in the ith cluster, q is the calculation coefficient per each fuzzy component, vi is the cluster core version I'd 2 (xk, vi) is the cluster dimension. [19].

d) K-Means Clustering with Median Filter

This is the proposed approach where K-means is really a search technique, and the centers of the final clusters rely on the collection of original centers. An important part of the clustering is having well-chosen initial centers. We were using the methodology mentioned in [6] to find good initial centers that partition the set of data across the data axis with maximum variability. a key challenge is to find an unmounting point with both the highest variation on the data axis that would decrease the overall segmentation error. K-Means clustering technique is an unmonitored technique that is used to segment the area of interest from the context. It clusters or partitions the data provided into K-clusters or K-centroid-based pieces. The median filtering procedure is done via sliding a window over most of the files. The filtered image is produced by putting the value median at the output image in the input window at the middle position of that window. In the case of Laplacian noise distribution, the median is the highest frequency estimator of position. The median filter calculates the gray-level value for relatively uniform regions, with strong effectiveness when long-tailed noise is present. When an edge is crossed, the window is occupied by either side, and the display changes abruptly between the values. The bottom isn't blurry, though. The median filter value is g(x, y)=med{f(x-i, y-j),i, j, jww where the original image & reference image are f(x, y) g(x, y) respectively [20].

C. Proposed Algorithm

In the proposed methodology we will follow some steps that are involved in image segmentation using the approaches are described below:

Step 1: Take any original image sample(RGB image)
Step 2: Initially RGB image are translated to HSV
Step 3: Apply the Otsu method for Image histograms assuming the bimodal distribution
.Step 4: Apply Fuzzy c-means algorithm.
Step 5: Median filtering with K-means algorithm where the picture is broken through K clusters of pixels of these same characteristics. Step6: Get an improved segmented image.

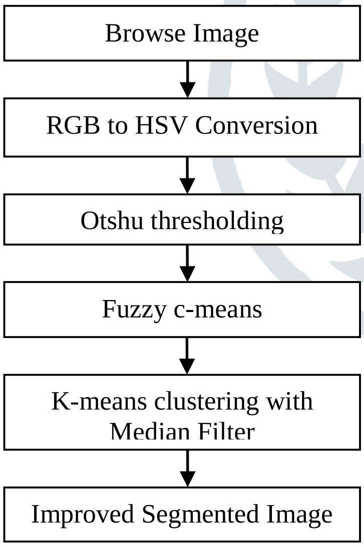

Figure 1: Proposed Model

IV. Experimental Analysis

The simulation of the proposed work was done by analyzing a sample image with a Matlab tool. In this work, we ensemble fuzzy c means with median filtering with a k-means algorithm. Visual research provides a strong indicator of Median filter with K-means showing the best performance to the degree that the commonality Index and Tanimoto Equations are being used as empirical criteria, og different methods. SI & TC also Test the resemblance of the differentiated items by correctly calculating the number of foreground pixels. SI & TC values vary from 0 - 1. A high value is equivalent to 1 which means that the higher picture quality was nearest to 1.

A. First, we run our program and get the output as

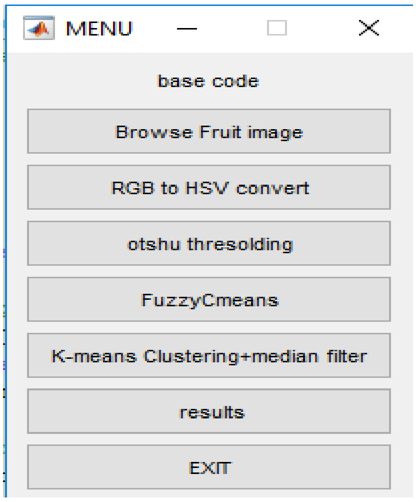

Figure 2: Browse Image

In the above figure firstly we browse an original sample image (fruit)

B. Convert RGB image it to hsv image

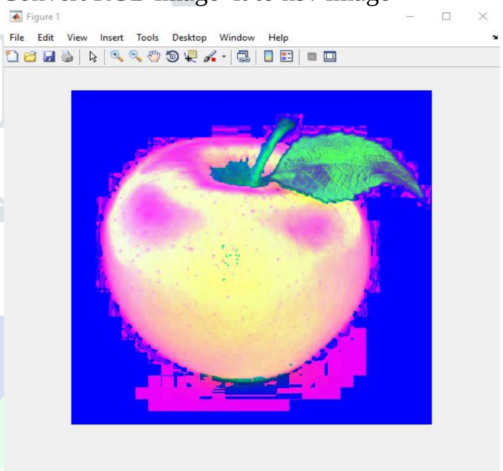

Figure 3: Conversion of RGB TO HSV

The above figure defines that at first the RGB image is translated to the picture, HSV and afterward the color-based optimization is implemented which effectively identifies the fruit.

C. Applying Otsu thresolding

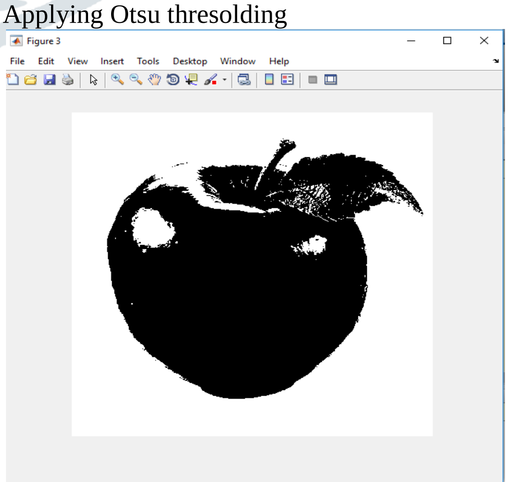

Figure 4: Output Image of Otsu thresholding

The above diagram shows the output image after the Otsu thresholding.

D. Applying K means clustering

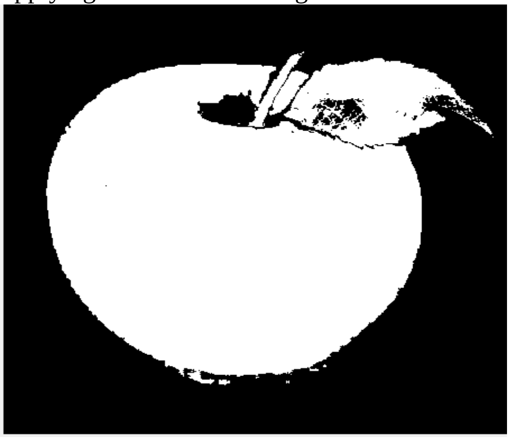

Figure 4(i): Output Image of K means clustering phase 1

Figure 4(ii): Output Image of K means clustering phase2

Figure 5: Output Image of K means clustering with a median filter

E. Applying k means clustering

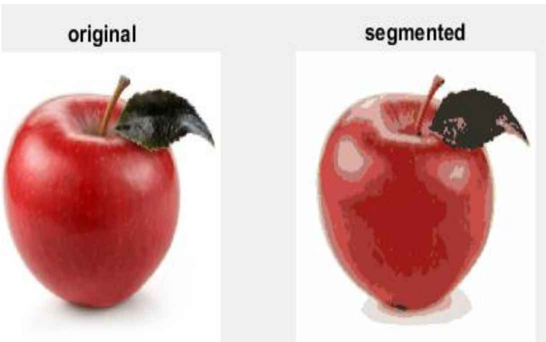

Figure 6: Improved segmented Output picture

Table 1: Index of Similarity (S.I.) and Coefficient Tanimoto (T.C.) use different techniques.

Techniques	Tanimoto Coefficient (TC)	Similarity Index (SI)
Otsu Thresholding	0.9530	0.5326
Fuzzy C-means	0.0303	0.0738
K means clustering+median filter	0.0188	0.9034

That table provides a picture of using strategies with the Similarity index and Tanimoto Coefficients.

V. CONCLUSION & FUTURE SCOPE

In addition, K-means with a median filter system provides excellent results in the segmentation and identification of virtually any kind of object that has different, sizes, shapes & functions including under natural lighting. Can one probably make a study for various fruits for differentiated pictures from effects is above the proposed method? The integrated HSV conversion algorithms and median filter perception with a k-means system on HSV picture need capacity to evaluate & discern the area's value, as well as of information of background. A suggested technique focuses on fruit identification optimization is based conducted a fruit picture. Fruit identification is another stage that can be applied After observation, with a few surface & fruit color-related information Still, we can accurately classify the fruit under analysis using a machine learning program such as ANN. The paper proposes a basic but efficient algorithm for the segmentation of images. According to Simplicity, good efficiency and powerful clustering characteristics, the k-means algorithm is used in the segmentation-based median filter. The results of the experiment suggest that its efficiency would be much more complex, close to the success of equations.

REFERENCES

[1] M. Tang, L. Gorelick, O. Veksler, and Y. Boykov, "Grabcut in one cut," in IEEE International Conference on Computer Vision, 2014, pp. 1769–1776.

[2] H. Wang, B. Wang, Z. Zhou, L. Song, S. Li, and S. Wu, "Region fusion and grab-cut based salient object segmentation," in Sixth International Conference on Intelligent Human-Machine Systems and Cybernetics, 2014, pp. 131–135.

[3] A. Wong, "Adaptive bilateral filtering of image signals using local phase characteristics," Signal Processing, vol. 88, pp. 1615-1619, Jan. 2008

[4] B. Zhang and J. P. Allebach, "Adaptive bilateral filter for sharpness enhancement and noise removal," IEEE Trans. on Image Process., vol. 17, no. 5, pp. 664-678, May 2008

[5] L. Sun, O. C. Au, R. Zou, W. Dai, X. Wen, S. Li, and J.Li, "Adaptive bilateral filter considering local characteristics," in IEEE Conference on Image and Graphics, 2011, pp. 187-192

[6] Mignotte, Max., "A de-texturing and spatially constrained K-means approach for image segmentation." Pattern Recognition Letters, 2010

[7] Y. Li, J. Zhang, P. Gao, L. Jiang, and M. Chen, "Grab Cut Image Segmentation Based on Image Region," *2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC)*, Chongqing, 2018,pp.311-315.doi: 10.1109/ICIVC.2018.8492818

[8] W. Wang, H. Sheng, S. Liu, Y. Chen, J. Wan and J. Mao, "An Edge-Preserving Active Contour Model with Bilateral Filter based on Hyperspectral Image Spectral Information for Oil Spill Segmentation," *2019 10th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS)*, Amsterdam, Netherlands, 2019, pp. 1-5. DOI: 10.1109/WHISPERS.2019.8921042.

[9] Z. Chen, J. Jiang, C. Zhou, S. Fu, and Z. Cai, "SuperBF: Suprpixel-Based Bilateral Filtering Algorithm and Its Application in Feature Extraction of Hyperspectral Images," in *IEEE Access*, vol. 7, pp. 147796-147807, 2019.doi: 10.1109/ACCESS.2019.2938397

[10] Y. Zhang, F. Shi, J. Cheng, L. Wang, P. Yap, and D. Shen, "Longitudinally Guided Super-Resolution of Neonatal Brain Magnetic Resonance Images," in *IEEE Transactions on Cybernetics*, vol. 49, no. 2, pp. 662-674, Feb. 2019.doi: 10.1109/TCYB.2017.2786161

[11] P. Zhang and L. Kong, "Wheel Defect Segmentation Based on Improved Otsu Method," *2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP)*, Shenzhen, 2018, pp. 231-235. DOI: 10.1109/SIPROCESS.2018.8600467

[12] Q. Hou and C. Jung, "Occlusion Robust Light Field Depth Estimation Using Segmentation Guided Bilateral Filtering," *2017 IEEE International Symposium on Multimedia (ISM)*, Taichung, 2017, pp. 14-18. DOI: 10.1109/ISM.2017.13

[13] J. Wang, J. Wu, Z. Wu, G. Jeon, and J. Jeong, "Bilateral Filtering and Directional Differentiation for Bayer Demosaicking," in *IEEE Sensors Journal*, vol. 17, no. 3, pp. 726-734, 1 Feb.1, 2017. DOI: 10.1109/JSEN.2016.2623422

[14] A. K. Gautam and M. R. Bhutiyani, "Performance evaluation of Hyperspectral image segmentation implemented by recombination of PCT and Bilateral filter based fused images," *2016 3rd International Conference on Signal Processing and Integrated Networks (SPIN)*, Noida, 2016, pp. 152-156. DOI: 10.1109/SPIN.2016.7566679

[15] https://www.geeksforgeeks.org/program-change-rgb-color-model-hsv-color-model/

[16] Yousefi, Jamileh. (2015). Image Binarization using Otsu Thresholding Algorithm. 10.13140/RG.2.1.4758.9284.

[17] Dunn, J. C.: A Fuzzy Relative of the ISODATA Process and its Use in Detecting Compact Well Separated Clusters. Journal of Cybernetics, Vol. 3, 1974, pp. 32–57.

[18] Bezdek, J. C.: Pattern Recognition with Fuzzy Objective Function Algorithms. New York: Plenum Press, 1981.

[19] Yong Yang, Shuying Huang," Image Segmentation By Fuzzy C-Means Clustering Algorithm With A Novel Penalty Term", Computing and Informatics, Vol. 26, 2007, 17–31,pp.1-15.

[20] Youlian Zhu, Cheng Huang," An Improved Median Filtering Algorithm for Image Noise Reduction", 2012 International Conference on Solid State Devices and Materials Science, Physics Procedia 25 (2012) 609 – 616.