

Histogram based Data Fusion Approach for Image Segmentation

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Abstract— This paper presents the problem formulation and an approach for the image segmentation using histogram-based data fusion. Presented approach involves the evaluation of histograms of three independent planes with the block-based processing. Each plane image is processed through the blocks of similar size. Then, similar blocks are identified for each plane based on the peaks and downs. Matched blocks peaks and downs are used to identify the threshold value for the matched blocks. This paper may be useful for the beginners in the research domain of image segmentation.

Index Terms—Image segmentation, Histogram, Data Fusion, Thresholding

I. INTRODUCTION

Image segmentation is the problem which is well known in image processing. One can identify different regions in the image by using the different image segmentation algorithms. Well known technique for image segmentation is the thresholding technique, through this one can identify different regions in the given image. Image segmentation [1] is considered as an important basic operation for meaningful analysis and interpretation of acquired images [2-3].

This paper discusses the different research work reported in literature along with the formulation of the problem with the possible approach for image segmentation which is based on the histogram-based data fusion. Data fusion is the term which is generally used to fuse the different type of data associated with the particular happening.

The paper is organized as follows. Section II discusses the summarized representation of the studied research papers. Section III elaborates the problem formulation and the proposed histogram-based data fusion approach is discussed in section IV. Experimental results are discussed in section V. Conclusion and future scope are provided in section VI followed by relevant references.

II. RELATED WORK

It is a classic inverse problem which consists of achieving a compact region-based description of the image scene by decomposing it into meaningful or spatially coherent

regions sharing similar attributes. Over the last few decades, several segmentation techniques, either in gray level or color images, were presented in literature and many methodologies have been proposed. There is still no segmentation technique that can dominate the others for all kinds of color images yet [4-5]. Our interest in this study is to segment color images with the desire of optimality. Many different techniques have been developed for this purpose. Some formulations have been expressed by Harrabi and Ben Braiek [6] and Ben Chaabane et al. [7]. In the most of the existing color image segmentation approaches, the definition of a region is based on similar color. Monochrome image segmentation techniques [8] can be extended to color image, by using the RGB color space or their transformations (linear/nonlinear).

Image segmentation is an important signal processing tool that is widely employed in many applications including object detection [9], object-based coding [10-12], object tracking [13], image retrieval [14], and clinical organ or tissue identification [15]. To accomplish segmentations in these applications, the methods can be generally classified as region-based and edge-based techniques. The region-based segmentation techniques such as semi supervised statistical region refinement [16], watershed [17], region growing [18], and Markov-random-field parameter estimation [19] focus on grouping pixels to become regions which have uniform properties like grayscale, texture, and so forth. The edge-based segmentation techniques such as Canny edge detector [20], active contour [21], and edge following [22-24] emphasize on detecting significant gray-level changes near object boundaries. Regarding to the above-mentioned methods, the segmenting mechanisms associated with users can be further categorized as either supervised segmentation or unsupervised segmentation. An ideal segmentation method should have a classification rate of 100% and a false detection rate of 0%. In fact, the adaptation of segmentation techniques to different color images remains as a challenging task.

A. Image Segmentation and Data Fusion

Though Thresholding is a known image segmentation method considering the frequent problem of thresholding since years, it has its own computational difficulties. Novel multilevel thresholding method based on particle

swarm optimization (PSO) plays a vital role in maximizing Kapur's and Otsu objective functions. Segmentation of grey level image and MRI scans uses the optimal thresholding techniques making it effective and applicable [25].

FISH Technique [26] produces new multi-level thresholding-based FISH signal segmentation method used for images. This widely used cancer diagnosis technique is based on chromosomal regions with specific dyes. Microscopes used at high resolution shows the segmentation of cell nuclei using this method. This gives adaptive thresholding, distance transform and watershed methods. The detection rate has varied in the course of times using FISH signals which were used on FISH images and has become higher than other widely used techniques.

Ludwig [27] proposes glowworm swarm optimization algorithm used in multilevel thresholding. The author identifies the GSO algorithm and shows results based on the current identification in comparison to basic GSO. Chen et al. [28] proposes eye gazing system using multilevel thresholding for pupil location. The author identifies a fusion method based on overlaps of segmentation results. The eye gazing is achieved by proposing methods in order to improve pupil location accuracy. Ali et al. [29] proposes Hybrid Differential Evolution Algorithm for Multi-level Image Thresholding. The author identifies Image thresholding for extracting objects from the background and discriminating objects from objects to have distinct gray-levels.

Ma et al. [30] proposes improved fireworks algorithm for Multi-level image thresholding by adopting fitness function, the global search and the local search for concurrent and efficient algorithms. Janudhivya et al. [31] proposes Mumford-shah algorithm for the detection of lung cancer cell. Mumford-shah model is applied and the author uses the algorithm to compute the feature vectors. Sun et al. [32] proposes Multilevel Thresholding and Nature-Inspired Algorithms for Grayscale Image Segmentation and states the GSA, GA and GSA-GA algorithm to identify optimal threshold values. Kuçukkulahlı et al. [33] proposes automatic segmentation of images which are Histogram-based. The author specifies k-means clustering possible centroids of the clusters and the optimum cluster number. The segmentation problem is resolved till an extent by using histogram and k-means clustering method. Jung [34] proposes L1 data fidelity measures and assume that an image can be approximated by the sum of a piecewise-constant function and a smooth function. Signifying the L1 data-fitting terms enable to segment images. The author identifies the augmented Lagrangian method and presents a partial convergence result.

Ali et al. [35] proposes Hybrid Differential Evolution Algorithm for Multi-level Image Thresholding. The

author identifies Image thresholding for extracting objects from the background and discriminating objects from objects to have distinct gray-levels. Dehshibi et al. [36] proposes hybrid bio-inspired learning algorithm using a combination of two pioneer methods, namely Otsu and Kapur's, are investigated to solve the threshold selection problem. Author identifies and uses object function and LA explores in the probability space, providing appropriate convergence properties and robustness. Shahid et al. [37] proposes coverage measurement in shot peening processes for real-time Image segmentation using, edge detection, watershed segmentation, active contour, and graph cut techniques. Sudhan et al. [38], proposes Optic disc segmentation based on Heuristic algorithm and level set approaches for guiding the multi-level thresholding for image similarity index values. Tuba et al. [39] proposes elephant herding optimization algorithm using Kapur's and Otsu's methods for representing a hard optimization problem and swarm intelligence algorithms for Multilevel image thresholding.

Pare et al. [40] proposes gray-level co-occurrence matrix and differential evolution algorithm for Color multilevel thresholding the gray level co-occurrence matrix (GLCM) and differential evolution (DE) algorithm that shows optimum result while iterations. Divya et al. [41] analysis of skin cancer using soft computing approach based on region extraction for suspicious regions which are recorded. Li et al. [42] proposes graph-based manifold ranking using Saliency detection: Multi-level combination approach and identifies that graph-based manifold ranking method cannot do well in highlighting the salient objects uniformly and suppressing the background effectively and also by comparing the method with the other eight state-of-the-art methods. Chandra et al. [43] proposes two different Convolutional Neural Network (CNN) to classify digits and letters in an automated system to detect and recognize vehicle license plates based on plate detection, extraction, character segmentation and recognition.

III. PROBLEM FORMULATION

A. Histogram

Histogram are, in general, used to represent the distribution of the intensity values in the given image. Color image used to have three histograms for three independent grey level planes.

B. Data Fusion

When we want to use multi type of data of particular thing then there is a need of fusion of data arises. To do this, the process adopted is called as data fusion. Data fusion involves the data from multi sources as well as the data of one particular image in the form of different features, color, statistics, etc.

C. Problem Formulation

We can process the given image by using the block-based processing. For each block, we can evaluate the histograms and later, based on the peaks and downs in the concerned blocks, we can match it with the other block histogram peaks and downs. Based on the matching, we can fuse the data in view of identification of the threshold.

The following symbols are used for the mathematical presentation of the identified problem. Let,

$I \rightarrow$ Original color image.

$IR \rightarrow$ R-grey level plane of color image I .

$IG \rightarrow$ G-grey level plane of color image I .

$IB \rightarrow$ B-grey level plane of color image I .

$IR_1 \dots IR_m \rightarrow$ Blocks of the R-grey level plane.

$IG_1 \dots IG_m \rightarrow$ Blocks of the G-grey level plane.

$IB_1 \dots IB_m \rightarrow$ Blocks of the B-grey level plane.

Image I is divided in three grey level planes, namely, IR , IG , and IB . Later each plane of IR , IG , and IB is divided in equal number of blocks (say, m). Therefore, IR is divided in IR_1 to IR_m number of blocks, likewise IG is divided in IG_1 to IG_m number of blocks, and IB is divided in IB_1 to IB_m number of blocks.

Now, the matching of IR_1 to IR_m is carried out based on the peaks and downs in the histogram of IR_1 to IR_m . the matching of IG_1 to IG_m is carried out based on the peaks and downs in the histogram of IG_1 to IG_m . the matching of IB_1 to IB_m is carried out based on the peaks and downs in the histogram of IB_1 to IB_m . Then, the threshold is evaluated for each matched blocks of the IR , IG , and IB grey level planes using data fusion.

IV. PROPOSED APPROACH

Histogram-based data fusion approach for image segmentation is shown in the Figure 1.

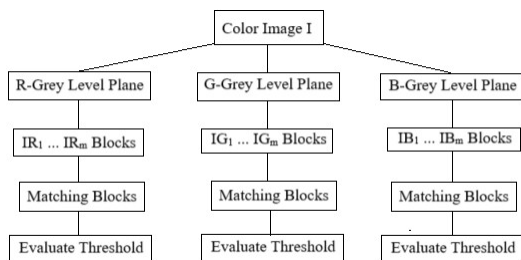


Figure 1: Possible Approach for Image Segmentation based on Histogram and Data Fusion

The complete procedure of the presented approach is as follows:

Step-1: Read the color image I .

Step-2: Separate three grey level planes *i.e.* IR , IG , and IB .

Step-3: Generate different number of blocks.

Step-4: Identify the peaks and downs for each block.

Step-5: Carry out the matching of the peaks and downs for each block

Step-6: Fuse the data of each matching block.

Step-7: Evaluate the threshold for similar blocks.

Step-8: Segment the concerned similar blocks.

Step-9: Get the segmented image based on Otsu's and multi-level threshold.

V. EXPERIMENTAL RESULTS

Experiments are performed on the standard images [44] with the System Type: x64-based PC, Processor: Intel(R) Core (TM) i3-2350 M CPU @ 2.30 GHz, 2300 MHz, 2 Core(s), 4 Logical Processor(s). Figure 2 shows the original House image and grey level plane images. Figure 3 represents the histogram of original House image and grey level planes. Figure 4 (a), Figure 4 (c), and Figure 4 (e) shows the Otsu threshold results and Figure 4 (b), Figure 4 (d), and Figure 4 (f) shows the multi-level threshold results for House grey level planes, respectively.

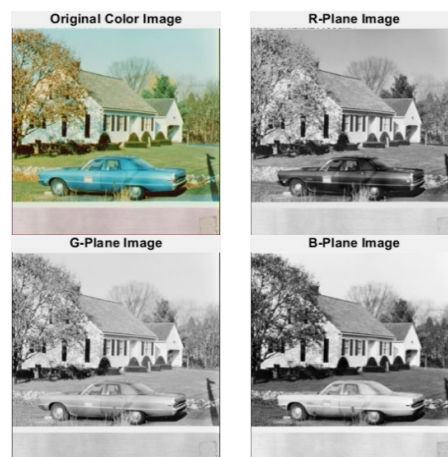


Figure 2: Original House Image and Grey Level Planes

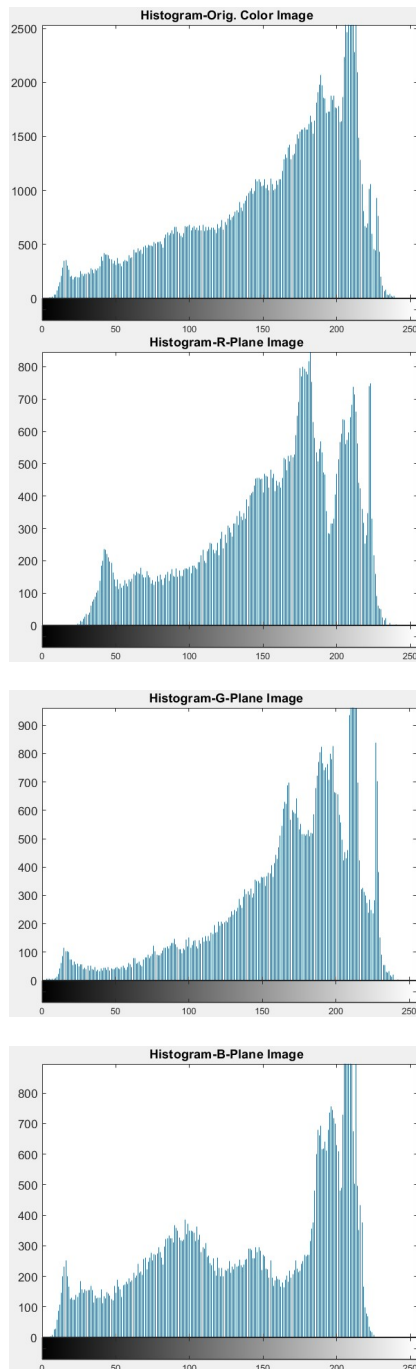


Figure 3: Histogram of Original House Image and Grey Level Planes

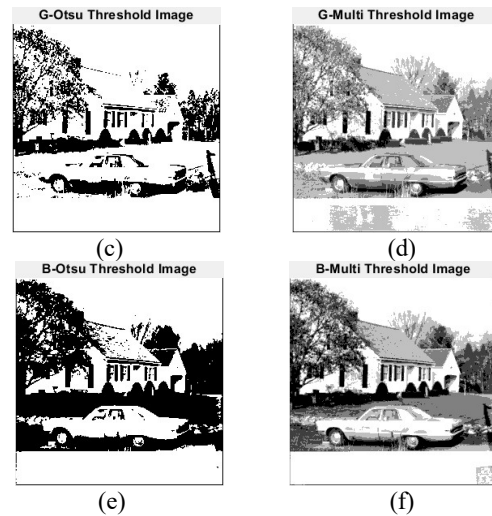
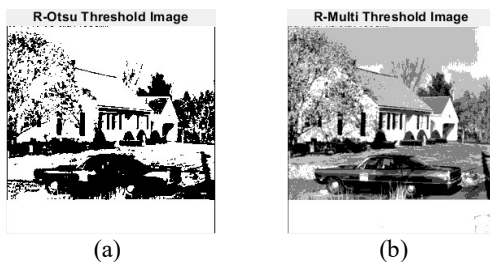


Figure 4: Otsu Threshold Results in (a), (c), (e) and Multi-Level Threshold Results in (b), (d), (f) for House

VI. CONCLUSION AND FUTURE SCOPE

Presented approach for image segmentation can be implemented for the color image by separating three grey level planes of the RGB color image. Later in future, the presented approach can be enhanced with the aggregate histogram-based multi-level thresholding in view of the image segmentation. This paper may be useful for the beginners in the domain of the image segmentation.

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