A Modified Watershed Algorithm for Image Over-Segmentation

Anuja Soni
Department of Computer Science
Deen Dayal Upadhyaya College
University of Delhi,
New Delhi, India

Manish Singh
Department of Computer Science
Acharya Narendra Dev College
University of Delhi
New Delhi, India

Rahul Dwivedi
Department of Computer Science
Acharya Narendra Dev College
University of Delhi
New Delhi, India

Sagar Patwal
Department of Computer Science
Acharya Narendra Dev College
University of Delhi
New Delhi, India

Vibha Gaur
Department of Computer Science
Acharya Narendra Dev College
University of Delhi
New Delhi, India

ABSTRACT
Image Segmentation has been successfully implemented in recent years, which has resulted in the evolution of many image retrieval applications and other image processing systems like medical imaging, object detection etc. There exists a plethora of image segmentation techniques and algorithms used in image processing. The Watershed approach is among the most prevalent techniques of image segmentation, which suffers from the problem of over-segmentation of the image. This article proposes a novel strategy for the preprocessing of the image before applying the Watershed Algorithm. This proposed methodology is computationally non-intensive and helps solve the problem of over-segmentation. The approach can reduce the count of initial seeds for the Watershed image segmentation in O(n) time, where n represents the count of pixels in the image, thus making it an ideal approach for the Watershed transform. To ensure the quality of the image using the suggested Modified Algorithm, this study does the pixel analysis and henceforth compares the results of the Standard Watershed Algorithm and the Proposed Modified Algorithm using metrics like Shannon Entropy (S_Entropy), Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), Average Difference (AD), Mean Absolute Error (MAE), and Connected-Components (CC). Based on the findings, it can be concluded that the high values of PSNR and S_Entropy, along with low MSE, AD, and MAE values, show good-quality images. Furthermore, the 66.6% reduction in CC in the final image obtained after the modified approach is another indicator that the over-segmentation has been reduced without compromising on image quality.

Keywords
Modified Watershed Algorithm, Image segmentation, Watershed Transformation, Initial Seeds, Over-Segmentation

1. INTRODUCTION
Image segmentation approaches have become more and more common in practice over the last few years because of their effectiveness in contributing to the construction of intelligent systems in many different scenarios. Image segmentation can benefit a variety of applications such as object recognition, medical image processing, image indexing and many more [1]. Different algorithms for image segmentation have been designed. In this study, it is seen that image segmentation serves as an essential base for many applications that exist in fields of science, such as computer vision, biometrics, feature extraction, and image recognition [2]. Conceptually, image segmentation is an act of subdividing an image into several sets of pixels such that the pixels in the same set exhibit common characteristics. Procedurally, the process of image segmentation involves assigning a specific value to each pixel in an image with a view to distinguishing between various areas of an image. Essentially, the distinction between the image regions is done on the three basic properties of an image, viz. color, intensity, and texture. Therefore, the selection of an image segmentation technique is done only after a thorough analysis of the problem domain that deserves further processing. As images provide visual as well as inferential information, it is crucial to segment an image based on domain-specific characteristics [3, 4].

The aim of this study is to offer an overview of various image segmentation techniques mentioned in academic literature. One of the challenges experienced when utilizing the commonly used Watershed technique for image segmentation is over-segmentation. The watershed algorithm is one of the region-based methods for segmenting images that are commonly used in image processing to distinguish different objects in an image. One main drawback of using the Watershed algorithm is over-segmentation. Over-segmentation occurs if the algorithm divides the image into too many small regions instead of dividing it into suitable objects. The reason behind over-segmentation is that the Watershed algorithm is very perceptive to noise, intensity change, textures, and local minima in the image, and hence it may produce many small basins [5, 6].

In the current paper, an improved preprocessing process before the application of the Watershed technique is suggested. The modified approach improves the problem of over-segmentation while saving on computing costs. The improvement makes a perfect match for the Watershed Transform algorithm since it reduces the number of seeds initially required for image segmentation in linear time.

This work makes the following contributions:

- This study proposes a novel strategy for the preprocessing of the image before applying the Watershed Algorithm, which reduces the noisy pixels and, henceforth, the erroneous regions from the image by eliminating initial saddle points that may exist in the color image due to varying intensities of colour contrast.

- The proposed algorithm does not require much computational effort; rather, it runs linearly in O(n) time, where n is the count of pixels in the image, while maintaining the quality of the image.
- The Standard Watershed Algorithm gives an equal weight to all the pixels, while the proposed modified algorithm gives more importance to the certain pixels or areas (like edges or objects) and hence can produce a good-quality image.
- The comparative analysis of results obtained from Standard Watershed Algorithm and Proposed Modified Algorithm is performed using S_Entropy, PSNR, AD and MAE. High PSNR with high values of S_Entropy along with low values of MSE, AD, and MAE indicates better image quality of the generated image.
- This work considerably reduces over-segmentation of the image. CC in the final generated image using the modified algorithm can act as another metric to indicate reduction in over-segmentation without deteriorating the quality of the image.

The paper has four other sections apart from the introductory, data availability and references section. The second section includes a literature survey on various image segmentation techniques and focuses especially on early approaches associated with improving the Watershed Algorithm. The third section describes a Modified Watershed Algorithm using improved preprocessing, whereby the input image is first processed in linear time to prepare it for use in the Watershed Transform. The modified approach may be considered an optimal one for preprocessing since it ensures fewer seeds and hence prevents over-segmentation within the Watershed Algorithm. The fourth section includes the findings of the experiment performed using different statistical parameters. The paper's conclusion is presented in the fifth section.

2. LITERATURE REVIEW

Various image segmentation algorithms [7, 8] have been developed for numerous problem-specific purposes. Graph-Based Segmentation (GBS) approaches [9] usually characterize the scenario in the form of a graph G = (V, E), where every node symbolizes a pixel and an edge connects it to its neighbours. A weight on an edge represents the image intensity or some other properties of an image, depending on the implementation. K-Nearest Neighbours Graph-based Segmentation [10] utilizes a graph data structure and selects a specified number of neighbours (k) based on some predefined properties like image intensity, color, etc. Rather than constructing the complete graph, only a small fixed number of neighbours for each point are analyzed, which results in O(n) edges for n pixels of an image and overall makes the algorithm's temporal complexity O($nlogn$). But it is operationally costly to identify the k proximate neighbours when the image size is extremely high.

The Dynamic Region Merging (DRM) algorithm-based image segmentation [11, 12] consists of two algorithms. The first algorithm uses a region merging predicate, and another algorithm takes the over-segmented image and performs the segment merging, iteratively, according to the merging predicate. To obtain an optimal solution, the method uses a dynamic programming approach. The advantage of this algorithm includes its ability to solve the two primary problems associated with the basic region merging algorithms viz. merging order and terminating condition of the algorithm. The pre-processing of an image results in a quicker process of integrating regions. Ever since the merger predicate is dependent on the dissimilarity among pixels having a common boundary of two regions, the need to reintroduce suppressed contours may be avoided. The Hybrid Image Segmentation (HIS) method [13] is a hybrid of some popular algorithms for segmenting images. The segmentation of images using this algorithm is performed in three steps: A Split-and-Merge approach is applied, where the image is partitioned and the similar histogram bins are calculated. The Histogram Clustering algorithm is used to segment the relevant image histogram bins. Finally, the method takes two different images and calculates the mutual information by applying the split and merge algorithms and histogram clustering algorithms for both the images. The major proponent of this algorithm is the lack of assumption of any prior information about the images like intensity, probability distribution, etc. The underlying algorithm performs Recursive Partitioning inefficiently in some situations, which requires a lot of time to reach the small targets in an image, thereby increasing the algorithm's execution time. The Watershed Image Segmentation (WIS) [14] utilizes the geographical narrative of the immersion process, where the image is considered immersed in the water to create the watershed. As the regions in the image have small variations in their gradient readings, the visual can be considered as a topographical surface. Corresponding to various minima(s), water floods the basins. Build a barrier between the two lines to prevent water from different areas coming from two different minima(s) from mingling. After the surface is completely submerged, the collection of lines that separate two basins makes the watershed of the image. A watershed contour, often known as a boundary, is a closed contour that precisely follows the edges of the watershed, i.e., it is made up of watersheds. The Modified Watershed Segmentation (MWS) for 2D images [15] eliminates extraneous regions and provides more distinct object borders. The technique uses region generation by suppressing insignificant local minima.

The abovementioned approaches have the following drawbacks:

a) Most of the methodologies suffer from the problem of poor over-segmentation of the image. On recursively applying unsupervised transformations, the algorithms may over-segment the image by introducing extraneous boundaries. The Modified Watershed Segmentation for 2D images [15] reduces the over-segmentation problem to some extent, but this is computationally complex and consists of sensitivity to marker generation.

b) Being sensitive to local minima, the segmentation process may be negatively impacted if the image has noisy pixels.

The Watershed Algorithm tends to introduce extraneous boundaries, thereby causing over-segmentation. The problem of over-segmentation in images has been addressed by some researchers. For instance, this over-segmentation in images can be processed by merging some of the basins by removing irrelevant watershed lines.

The extant approaches propose Image Component Labelling (ICL) [16], Multi-Scale Gradient Analysis (MSGA) [17], P Algorithm (P-A) [18], Graph-Clustering Method (GCM) [19], Deep Learning-Based Segmentation (DLBS) [20], Gradient Watersheds (GW) [21], Random Walk Preprocessing (RWP) [22], Curvlet Transform (CT) [23], Distance Map Reconstruction (DMR) [24], and Adjustable Masking and Thresholding (AMT) [25].

Mohamed et al. [16], Chen and Bovik [17], and Beucher and Marcotegui [18] used preprocessing through the conversion of the colored image into its grayscale equivalent before processing with Watershed Transformation for image segmentation. Gammoudi et al. [19] presented several image

segmentation algorithms formulated from the graph partition and provided the promising results. Bruns et al. [20] provided a thorough assessment of an automated technique for segmenting the heart chamber and left ventricular myocardium in 4D contrast-enhanced cardiac CT images using a sizable clinical dataset. Geremew et al. [21] used the process of preprocessing through the conversion of the colored image into its grayscale equivalent before processing with Watershed Transformation for image segmentation.

Sikander et al. [22] proposed an RWP on input images to improve the image contrast to improve segmentation results of the Watershed Algorithm. Hamdi et al. [23] proposed a stage of preprocessing that uses CT on input images. The divergence of images was improved by including CT, thus achieving a strong gradient for Watershed Segmentation and hence reducing over-segmentation. Liu et al. [24] applied DMR to increase the precision of adherent seed image segmentation. To lessen the gray area between the adzuki bean's seed coat and umbilicus and the potential for incorrect classification, morphological restoration was employed. The algorithm for concave point analysis found the concave points about the adherence between two seeds and matched them based on the smallest Euclidean distance to obtain precise segmentation. Rahman and Islam [25] employed AMT across each color channel before utilising the Watershed Algorithm. Segments from every channel were then combined to generate the final segmented image. This approach is successful in overcoming the over-segmentation of the Watershed Algorithm. These techniques, however, are based on predefined values, image assumptions, or high computing demands, all of which could affect the performance of the technique itself.

The Standard Watershed Algorithm has two major drawbacks.
a) The first is the problem of over-segmentation of the image. On recursively applying unsupervised watershed transformations, it becomes difficult to predict and control the optimal level of hierarchy, since successive segmentation may over-segment the graph display by identifying extraneous boundaries (contours).
b) The second drawback is a more severe form of the first drawback. When applying successive waterfall transforms, the intermediate recursions may not only add non-significant contours but also remove several significant ones.

This over-segmentation in images can be processed by merging some of the basins by removing irrelevant watershed lines. The proposed approach performs image preprocessing for noise removal and contrast enhancement before utilizing the traditional technique of Watershed Transformation for the purpose of over-segmentation prevention. This approach overcomes the problem of over-segmentation by introducing grayscale conversion and noise reduction in the preprocessing prior to the application of the Standard Watershed Algorithm.

3. MATERIALS AND METHODS

While processing images, the watershed algorithm is frequently used for image segmentation to identify various objects within an image but suffers with the over-segmentation problem. This paper proposes an enhanced pre-processing method prior to the application of the Watershed technique. The modified approach addresses the issue of over-segmentation and reduces computational cost. This improvement is well-suited to the Watershed Transform algorithm, as it decreases the number of seeds required for image segmentation in linear time.

In this article, the Modified Watershed Technique is employed to solve the problem of over-segmentation through initial preprocessing of the RGB image to an 8-bit per pixel (bpp) image. The input image is pre-processed by converting it into grayscale, thus reducing the possible noisy pixels that may be identified as erroneous regions by the Watershed algorithm. Each pixel's weight in grayscale is determined, considering the impact of color upon it. The image is pre-processed to reduce the effect of noise through grayscale conversion, followed by edge detection and Standard Watershed algorithms to produce the final segmented image.

The proposed Modified Watershed Algorithm contains the following phases:
1. **Image Pre-processing:** Pre-processing of an image is done to refine the image by reducing unnecessary details, complexity, or variations in an image while preserving its important structures, objects, and visual information. It consists of two sub-phases: **(i) Grayscale Conversion** and **(ii) Noise Reduction**. At this stage, the first step is to reduce the number of saddle points that exist in the colored input image due to different intensity levels of colors. The conversion helps reduce noisy pixels, which could otherwise be considered erroneous regions by the Watershed algorithm.

(i.) **Gray Scale Conversion**: Converting the input image to grayscale, also known as image simplification, is the first stage in the image processing pipeline. Due to the significant variations in intensity across the color channels, the grayscale transformation lessens the number of initial saddle spots that are frequently found in color images. This conversion is used to reduce noise by limiting the effect of spurious high frequency pixels which, if not treated, could be wrongly identified as separate regions in the watershed segmentation process. In the traditional pre-processing method of the Watershed algorithm, all pixels are given assigned weight, potentially overlooking salient features. In contrast, the optimized pre-processing strategy used in this study adaptively weights specific pixels or regions such as object boundaries and edge structures depending on their contextual importance. This kind of weighted approach leads to more precise segmentation and higher image quality, especially when there is complex scene content or heterogeneous intensity distributions. Moreover, this method also involves some additional morphological operations and adaptive filtering techniques to remove artifacts more efficiently and to enhance the definition of the anatomical or structural features of interest in the image.

(ii.) **Noise Reduction:** By using noise-reducing filters along with grayscale conversion, the Watershed algorithm's over-segmentation problem can also be mitigated. The proposed method eliminates unnecessary local minima that produces incorrect regions unrelated to the primary basis regions. Eliminating unnecessary local minima improves the algorithm's runtime performance and lessens the requirement for post-processing.

2. **Edge Detection:** Afterwards, an edge detection method [26] is employed on the pre-processed image to delineate object contours within digital images by detecting edges with local discontinuities in intensity values.

3. **Implementation of Standard Watershed Algorithm:** The standard watershed approach [27] is employed on the image with detected edges. The over-segmentation challenge in the context of a Watershed is handled using noise reduction filters together with image simplification techniques. This process helps eliminate the irrelevant local minima that would create irrelevant regions that do not belong to lower basins, thus eliminating the need for post-processing and minimizing the algorithm's running time.

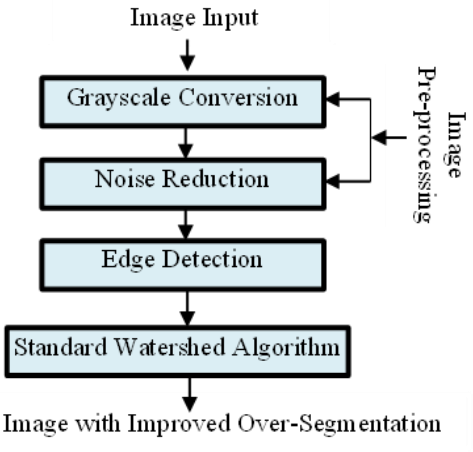


Fig 1: Various Stages of the Proposed Modified Watershed Algorithm

Figure 1 provides a schematic flow of segmenting an image using the proposed Modified Watershed Algorithm. The modification coded in Figure 1 may be understood by drawing an analogy of the correlation between successive pulses in signals and how it is exploited by differential pulse code modulation to encode an analog to a digital signal [28].

Algorithm 1 takes into account that the image may be in the continuous color space. Thus, the colors of similar shades will be close to the primary or combination of primaries (Red, Green, Blue) which forms the curved boundaries of the spectral figures. Hence, a particular color may have varying shades of gray in a grayscale image depending upon the illuminance or saturation of the color in the original-colored image. This varying, gray-shaded region may again be identified as a separate region after the Watershed Transformation. The pixel's grayscale value is varied with the contribution of a particular spectral color called the RGB color space in the color model. The weights added to a pixel value are based on the International Commission on Illumination (CIE) Standard color matching functions [29]. If one of the components has stronger intensity than the others, that color will contribute to the grayscale value with a weight equivalent to the percentage sum of the linear differences of that particular color with the other two colors. This added weight compensates for the variations of intensity of the same color due to different illuminance in different parts of the same image. The proposed modification works on the image pixel by pixel and hence completes the conversion in O(n) time, whereby n is the count of pixels in the input image.

Algorithm 1 Proposed Algorithm for Converting a Colored Image into Grayscale (for 8-bpp)

```
1: for each Pixel in image
2:         Red = Pixel.Red
3:         Green = Pixel.Green
4:         Blue = Pixel.Blue
5:         Gray = 0
6:         C1 = (Red-Green)
7:         C2 = (Green-Blue)
8:         C3 = (Red- Blue)
9:         if C1>0 && C3>0
10:                Gray= ((Red+ abs(C1)/100+ abs(C3)/100)*0.2126 + Green*0.7152 + Blue*0.0722)
11:        else if C2<0 && C3<0
12:                Gray= ((Blue+ abs(C1)/100+ abs(C3)/100)*0.0722 + Green*0.7152 + Red*0.2126)
13:        else if C1<0 && C2>0
14:                Gray= ((Green+ abs(C1)/100+ abs(C3)/100)*0.7152 + Red*0.2126 + Blue*0.0722)
15:        else       red*0.2126 + 0.7152*green + 0.0722*blue
17:        newPixel.Gray= Gray
18:     end if
19: end for
```

Given that the color "gray" has equal intensities of red, green, and blue components, each pixel can be specified with a single value. Generally, the grayscale intensities are stored as an 8-bit integer in the interval [0, 255] to represent black (0) to white (255). This algorithm also helps in stabilizing the variations in intensities by normalizing the values of successive pixels in the image. For noise reduction, a general noise model assigns arbitrary values dynamically in the range of 0 - 255 according to an underlying probability distribution. For a linear search on a 2D array, this method restores a noisy (256 x 256) image in a low execution time.

4. EXPERIMENTAL STUDY AND DISCUSSION

This section provides the implementation specifics of the proposed Modified Watershed Algorithm, which is validated using Pixel and statistical inferences.

4.1 Experimental Analysis

The proposed algorithm for grayscale conversion of an image was implemented in Python using OpenCV-Python libraries in MATLAB. The test image used in this study is shown in Figure 2(a). The test image is used to validate the proposed algorithm, considering two cases: the first one namely the Standard Watershed Algorithm does not consider the fuzzy noise reduction, while the Proposed Modified Watershed algorithm considers it. The over-segmented image is obtained after applying the Standard Watershed Algorithm as seen in Figure 2(b). The output of the Proposed Modified Watershed algorithm with the inclusion of fuzzy noise reduction is illustrated in Figure 2(c), whereas Figure 2(d) illustrates the finished image with grayscale markers. The greyscale markers are superimposed into the final image to create clean and accurate object boundaries without extra noise fragments.

4.1.1 Pixel Analysis

"Pixel analysis" refers to the use of quantification to measure changes in the pixel intensity value between the original and

the processed image. Pixel analysis in this study was performed using the measures Cross Information Entropy (CI_Entropy) and Weighted Cross Information Entropy (WCI_Entropy). CI_Entropy and WCI_Entropy are some metrics that are commonly used in image processing for analysis of the pixels [28]. The two metrics represent changes in the distribution of the pixels' intensities from the original image to the processed one. The Standard CI_Entropy metric gives an equal weight to all the pixels, while WCI_Entropy gives more importance to the certain pixels or areas (like edges or objects). These metrics are frequently used for evaluation of the segmentation of the image.

The metric CI_Entropy is computed by Equation 1:

$$CI_Entropy = -pd_1(x)\log\sum pd_2(x) \quad (1)$$

Where $pd_1(x)$ indicates the original image's probability distribution and $pd_2(x)$ represents the probability distribution of the segmented image.

The lower the value of CI_Entropy, the greater the fidelity of retention of vertex information maintained by the modified image.

The metric WCI_Entropy is computed by Equation 2:

$$WCI_Entropy = -w(x)\ pd_1(x)\log\sum pd_2(x) \quad (2)$$

Where $w(x)$ is the weight which emphasizes the intensity/importance of a region in the image.

Pixel values in the finished image obtained after the application of the Standard Watershed Algorithm and after applying the Proposed Modified Watershed Algorithm are demonstrated separately in Figure 3 (left-side image) and Figure 3 (right-side image).

The pixels of the image are shown along the horizontal axis, and the vertical axis displays the pixel intensity levels. In Figure 3 (left-side image), the effect of pixels may appear small because the background dominates, whereas in Figure 3 (right-side image), the object region gets larger weight, and hence, the change becomes noticeable.

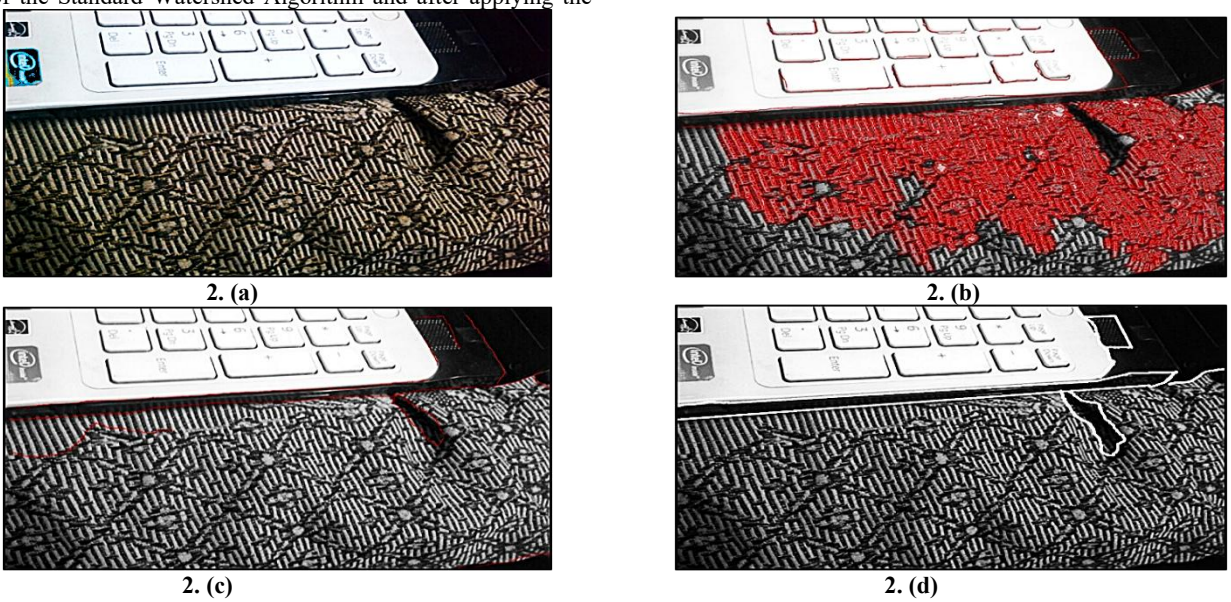
The weighted CIE image shown in Figure 3 (right-side image) is superior in terms of following characteristics.

1. **Higher Contrast and Edge Definition:** The tree trunk, branches, and foreground details are much sharper and clearly defined compared to the standard version.

2. **Reduced Visual Noise:** In Standard CIE, there is significant grainy noise ("salt-and-pepper"/speckled noise) scattered throughout the dark areas of the tree and foliage. Weighted CIE cleans up this speckling, resulting in smoother dark regions.

3. **Clearer Foreground-Background Separation:** The dark elements stand out better against the bright background sky and water.

Figure 4 displays the pixel histogram of the test image using the suggested method. A comparative study of pixels from the test image after applying the traditional Watershed Algorithm and the Modified Watershed Algorithm is shown in Figure 5.



2. (a) **2. (b)** **2. (c)** **2. (d)**

Fig 2: (a) Test image, (b) Over-segmented image after standard Watershed Approach (c) Intermediate Image after Proposed Watershed (d) Finished Image after Proposed Watershed with Grayscale Markers

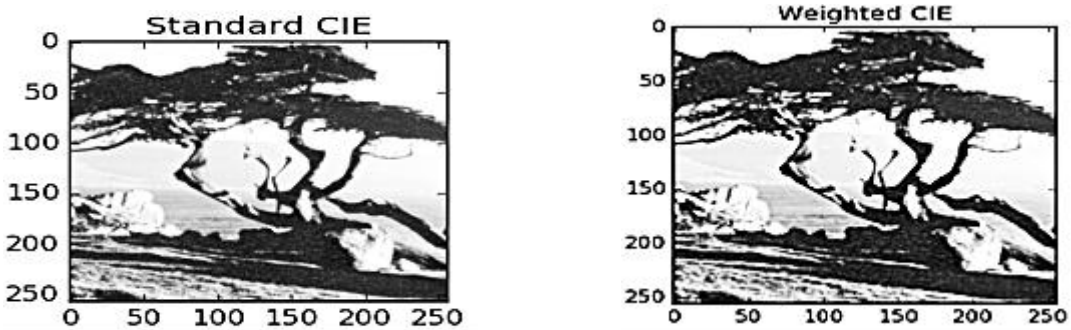


Fig 3: Grayscale converted image using Standard Watershed Algorithm (left-side image) and Grayscale converted image using the proposed modified Watershed Algorithm (right-side image)

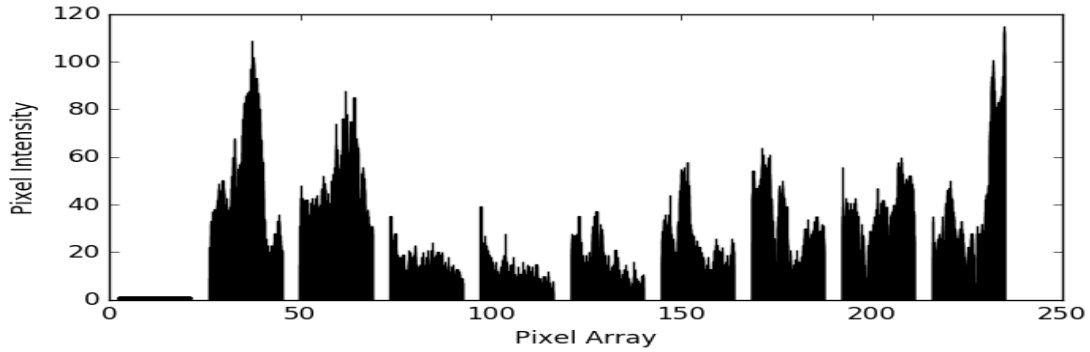


Fig 4: Pixel Histogram of Test Image using the Proposed Approach

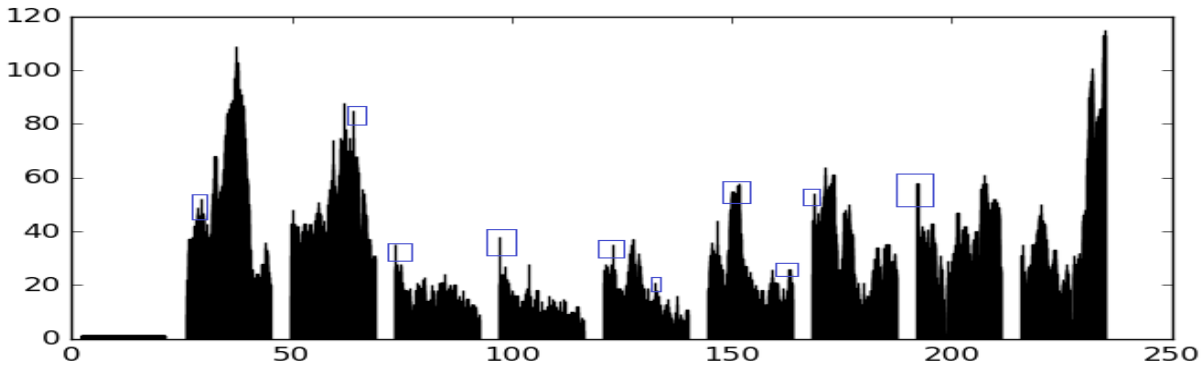


Fig 5: Comparative Analysis of Pixels

The blue rectangles in Figure 5 denote the differences in intensity values for the traditional Watershed Algorithm and the Modified Watershed Algorithm. Only those regions where there was one pixel having a high intensity value were normalized.

4.1.2 Statistical Inferences

Zaini et al. use statistical measures MSE, AD and MAE for objective qualitative assessment to compare images. The metrics such as S_Entropy, PSNR and CC are also used to validate the proposed algorithm [28].

I. **Shannon's Entropy (S_Entropy):** It helps to assess information in an image. S_Entropy for a grayscale image is computed using Equation 3.

$$S_Entropy(x) = -\sum_{x=1}^{n} p(x) log p(x) \qquad (3)$$

Where n is the gray level count and p(x) is the probability that a pixel will have gray level x.

A higher value of S_Entropy would mean that the more image details have been preserved. For image improvement and restoration, a higher value of Entropy is frequently regarded as desirable for image repair and enhancement.

II. **Peak Signal-to-Noise Ratio (PSNR):** It is described as the ratio of the greatest power pixel (image intensity) to the power of noise that causes image distortion. The value of PSNR is obtained using Equation 4.

$$PSNR = 10\ log_{10}\left(\frac{Max_f^2}{MSE}\right) \qquad (4)$$

Where Max_f is the greatest value of pixel intensity in the original image. When PSNR is high, it means the quality of the image is high.

III. **Mean Square Error (MSE):** The mean of the square of the variations between the pixel values in the original and final images is known as the Mean Square Error (MSE) and can be evaluated using Equation 5.

$$MSE = \frac{1}{pq}\sum_{k=0}^{p-1}\sum_{l=0}^{q-1}\left(f(k,l) - g(k,l)\right)^2 \qquad (5)$$

Where f is the original image's pixel matrix, g is the resulting image's pixel matrix, p is the number of image rows, q is the number of image columns, k is the row index, l is the column index, $f(k,l)$=pixel intensity at position (k, l) in image f, $g(k,l)$=pixel intensity at position (k, l) in image g.

Low values of MSE suggest low squared differences between the modified and the original images, which means better image reconstruction quality.

IV. **Average Difference (AD):** It is the average of the difference between the two images being compared and is computed using Equation 6.

$$AD = \frac{1}{pq}\sum_{k=1}^{p}\sum_{l=1}^{q}(f(k,l) - g(k,l)) \qquad (6)$$

where f is the test image, and g is the image being compared, p and q are the number of image rows and columns respectively. Low AD indicates a better retention of the original image properties, which suggests that the modified image has lower deviation from the target image in terms of intensity.

V. **Mean Absolute Error (MAE):** It is the absolute difference between the two images being compared. It is calculated using Equation 7.

$$MAE = \frac{1}{pq}\sum_{k=1}^{p}\sum_{l=1}^{q}|(f(k,l) - g(k,l))| \qquad (7)$$

Where f is the test image, and g is the image that is being compared. Low MAE indicates lower average differences of

pixel-wise comparisons between the modified and the original images, which means better image reconstruction quality.

VI. **Connected Components (CC):** CC of an image are those pixels that are adjacent to each other with pixels having similar intensity values. Counting the number of objects in a segmented image is made easier by computing its CC. The smaller the CC value, the less fragmented the image and the fewer segmented regions, resulting in less over-segmentation.

The performance of the proposed Modified Watershed algorithm is compared with the Standard Watershed algorithm using previously described metrics. The values of PSNR, MSE, AD, MAE and S_Entropy were calculated for the image obtained after applying Standard Watershed algorithm and for the finished image after applying the proposed Modified Watershed algorithm with Grey Scale Markers. The results are shown in Table 1.

Table 1. Statistical Comparison of Standalone Watershed Algorithm and Modified Watershed Algorithm

Statistical Measure	Image after applying the Standalone Watershed Algorithm	Finished Image after applying proposed Modified Watershed Algorithm with Grey Scale Markers
PSNR	5.8406319	5.8409978
MSE	16944.047965	16943.20010
AD	107.197956	107.143459
MAE	107.198065	107.143557
S_Entropy	7.209	7.3351

It was observed that there was an improvement in image quality obtained through the proposed Modified Watershed algorithm. Results indicated an increased value of PSNR by 0.0063% and slight improvements in error terms such as MSE by 0.0049%, AD by 0.0515%, and MAE by 0.0508%. It was also seen that the S_Entropy of the image obtained after applying the proposed Modified Watershed Algorithm increased by 1.75% in comparison to the image obtained after applying the Standard Watershed Algorithm, which is an indication of an enrichment in the excellence of the resultant image. The improved value of S_Entropy also indicates that the obtained image contains more information compared to the one obtained with the help of the standard watershed algorithm.

Further, the screenshot of computation of CC for the Test image is shown in Figure 6.

```
size = image.size
draw = ImageDraw.Draw(image)
pixels = image.load()
size = image.size
draw = ImageDraw.Draw(image)
i = 0
for x in range(0, size[0], 100):
    for y in range(0, size[1], 100):
        if pixels[x, y][1] > 200:
          i = i + 1
          draw.text((x, y), str(i), (255, 0, 0))


image.save('CCTest.png')
print("Connected Components of Test")
print(i)
```

Fig 6: Computing Connected Components (CC)

The values of CC were obtained as 6, 2, 4, and 2 respectively for the test image (Figure 2(a)), for the image obtained after applying Standard Watershed algorithm (Figure 2(b)), for the intermediate image after applying the Modified Watershed algorithm (Figure 2(c)), and the finished image after applying the Modified Watershed algorithm with Grey Scale Markers (Figure 2(d)). The 66.6% reduction in CC in the final image is another indicator that the over-segmentation has been reduced.

5. CONCLUSION

Image segmentation involves segmenting an image into regions using certain intrinsic features and components contained within the image. The Watershed Segmentation algorithm has gained popularity due to its widespread application; however, it suffers from over-segmentation. Several types and variations of this algorithm have been studied in this article, and a novel, Modified Watershed approach has been proposed to overcome the problem of over-segmentation. This modified algorithm runs in linear time complexity concerning the size of the image using the advantages of single-valued grayscale representation, and it also helps normalize the pixel intensity. After implementing this modified algorithm, the problem of over-segmentation was largely addressed. The proposed approach achieved a significant reduction of 66.6% in CC of the final image, which is an indication that over-segmentation has been reduced without compromising image quality. Moreover, the quality of the image got reasonably improved due to the higher values of PSNR and S_entropy metrics along with the lower values of MSE, MAE, and AD metrics.

6. DATA AVAILABILITY

The test image used in this study is obtained from external sources and not publicly available.

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