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AN IMPROVED WATERSHED ALGORITHM FOR MEDICAL IMAGE SEGMENTATION

***Dr. Ajala Funmilola A., Falohun A. S. and Opasola T. O.**

Department of Computer Science and Engineering, Faculty of Engineering and Technology, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.

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***Corresponding Author**
Dr. Ajala Funmilola A.
Department of Computer Science and Engineering, Faculty of Engineering and Technology, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.

ABSTRACT

This paper improves watershed segmentation algorithm to overcome its over-segmentation challenges using wavelet transform method at its post- possessing stage. The existing and improved algorithms (watershed algorithm and the improved watershed algorithm) were tested on medical images and comparative analysis in terms of segmentation accuracy, segmentation time and memory consumption was considered. Thirty (30) medical images were used for analysis and the average percentage of segmentation accuracy, segmentation time and memory consumption for existing watershed are 35%, 53% and 53%, respectively. The average percentage of segmentation accuracy, segmentation time and memory consumption of improved watershed for thirty (30) medical images are 65%, 47% and 47%, respectively. Based on the results obtained, the accuracy of the improved watershed was 30% higher than existing watershed while the segmentation time and memory consumption of the existing watershed is lower than the improved watershed by 6% and 6%, respectively.

KEYWORDS: Watershed Algorithm, Segmentation, wavelet transform.

1. INTRODUCTION

Harvey and Cohen (1996) reported that segmentation is the process of labeling pixels belonging to the same region. Image segmentation is used to locate objects and boundary in an image and each pixel in a region are similar with respect to some characteristics or properties, such as color, intensity, or texture (Lamia and Walid, 2009). There are different types of segmentation algorithms and some of these algorithms have gained ground in medical image analysis.

Grau, Mewes, Alcañiz, Kikinis and Warfield (2004) posited that watershed transform has an absorbing characteristics that made it different from other image segmentation applications; it is simple and intuitive, can be parallelized and always produce a complete division of the image. Also, when applied to medical image analysis it has important disadvantages (over-segmentation, sensitivity to noise, and poor detection of thin or low signal to noise ratio structures).The watershed segmentation algorithm produces an over-segmentation result of the image, but always contain contours that appear to be accurate.

According to Sifuzzama, Islam and Ali (2009); Meyer and Beucher (1990); Lokenath (2002); Ali (2014);Fedora and Jagadanand (2014),Wavelet analysis is a concept used in mathematics, physics, and engineering with modern applications such as wave propagation, data compression, signal processing, image processing, pattern recognition, computer graphics, the detection of aircraft and submarines and other medical image technology to solve difficult problems (part of which is over- segmentation) also, it allows complex information such as music, speech, images and patterns to be broken down from complex form to simple forms at different positions and scales and afterwards assembled with high precision.

The broad aim of this project is to improve watershed segmentation algorithm to overcome its over-segmentation challenges using wavelet transform method at its post- possessing stage, Segment medical images using existing watershed algorithm and develop an improved watershed algorithm using wavelet transforms. Medical images have been segmented using different segmentation methods. One of these methods is the watershed algorithm and in order to segment images, an enormous number of regions are located in watershed regions by finding the gradient magnitude of the thereby leading to over-segmentation. Also, over-segmentation can arise due to noise, small fluctuations in the image gray value which produce false gradient. Therefore there is need to reduce the problem of over segmentation.

Jung (2007); Claudio (2007);Grau *et al*. (2004); Meyer (1998)proposed different methods by introducing leveling approach which comprises morphological filters to reduce small details in the image and an edge-preserving statistical noise reduction approach as a pre-processing for the watershed transform for solving the problem of over-segmentation. Despite their modifications, there is a problem of noise in the segmented images.Hence, this work focused on improving watershed segmentation algorithm to overcome its over-segmentation challenges using wavelet transform algorithm at its post- processing stage.

2. LITERATURE REVIEW

Ajala, Fenwa, and Aku (2015) worked on Comparative Analysis of Watershed and Edge Based Segmentation of Red Blood Cells, a red blood cell image was analyzed using watershed transformation, and edge based segmentation; their corresponding results were compared. In terms of simulation time and correlation, watershed transformation performs better, but in terms of mean and deviation, edge based segmentation performs better.

According to Hill, Canagarajah and Bull (2013), the merits of the watershed transformation are; it always provides a closed contour which is very useful in image segmentation and requires low computation times in comparison with other segmentation methods (Lamia *et al*., 2009). The main advantages of the watershed method over other previously developed segmentation methods are the resulting boundaries form closed and connected regions (Hill *et al*., 2013; Rekha *et al*., 2015; Devanathan *et al*., 2016).

Edge based techniques most often form disconnected boundaries that need post-processing to produce closed regions and the boundaries of the resulting regions always correspond to contours which appear in the image as obvious contours of objects (Hill *et al*., 2013; Devanathan *et al*., 2016). In contrast to split and merge methods where the first splitting is often a simple regular sectioning of the image leading to unstable results and the union of all the region forms the entire image region (Hill *et al*., 2013; Rekha *et al*., 2015; Devanathan *et al*., 2016; Niket and Ramesh, 2013).The demerit of the watershed transform is excessive over segmentation (Niket *et al*., 2013; Hill *et al*., 2013), sensitivity to noise, poor detection of significant areas with low contrast boundaries and poor detection of thin structures (Anitha and Baskaran, 2015).

Anitha *et al*.(2015); reported that watershed transform has been widely used in many fields of image processing, including medical image segmentation, due to the number of advantages that it possesses; it is a simple intuitive method, it is fast and can be parallelized and an almost linear speedup was reported for a number of processors up to 64) and it produces a complete division of the image in separated regions even if the contrast is poor, thus avoiding the need for any kind of contour joining. It is appropriate to use this method to segment the high-resolution remote sensing image.

2.1 Watershed Algorithm

Watershed algorithm is described in details as follows by (Kolade *et al*., 2014):

Watershed segmentation has a weakness of over-segmentation. This was experienced after the segmentation has been done.

This was done after computing the distance transform of the complement of the binary image

$$D = bwdist(\sim Bw) \quad (2.1)$$

After which it complemented the distance transform and force pixels that do not belong to the objects to be at negative infinity

$$D = -D \quad (2.2)$$

$$D(-Bw) = negativeinfinity$$

At this stage, output image, has been over segmented.

These steps represent existing watershed algorithms

Step 1: *Let f: D → N be a digital grey value image, with hmin and hmax the minimum and maximum value of f.*

Step 2: *Let Xh denote the union of the set of basins computed at level h.*

Step 3: *A connected component of the threshold set Th+1 at level h + 1*

Step 4: *Computes the geodesic influence zone of Xh within Th+1*

Step 5: *Update Xh with Xh+1.*

Step 6: *Minh denote the union of all regional minima at altitude h.*

Step 7: *Compute* $Xh+1 = Minh+1 \cup IZTh+1\ (Xh)$, *h* $\in [hmin;\ hmax$

Step 8: *Compute Wshed (f) = D* $Xhmax$ *Watershed f is the complement of Xhmax inD.*

2.2 Wavelet Transform

According to Debnath, (2012); Ali and Mohamed, (2014), wavelet analysis can be defined as a mathematical technique that is used to represent data or functions,and it isfor solving difficult problems in mathematics, physics and engineering with modern applications such as wave propagation, data compression, signal processing, image processing, pattern recognition, computer graphics, the detection of aircraft and submarines and other medical image technology (Debnath, 2012; Ali and Mohamed, 2014). It allows complex information such as music, speech, images and patterns to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision; (Sifuzzaman, Islam, and Ali ,2009;Debnath, 2012; Ali and Mohamed, 2014).

Fourier transform is a powerful tool for analyzing the components of a stationary signal which cannot be used to analyze non stationary signal whereas wavelet transform allows the components of a non-stationary signal to be analyzed (Sifuzzaman *et al.*, 2009; Priyadharshini, Hans, Naresh and Swathy, 2013). It is also an improved version of Fourier transform (Fathima, Nisha and Sathik, 2016).

According to Lee, the steps involves for wavelet transform were;

2.3 Algorithm for Wavelet function

The discrete wavelet coefficients can be obtained by expanding wavelet function equation

$$W_{\emptyset}(j_{0,}\ k) = \frac{1}{\sqrt{M}}\sum_{x=0}^{M-1} f(x)\varphi_{j0,k}(x) \qquad (2.3)$$

Where,

j ≥ j and the $W_{\emptyset}(j_{0,}\ k)$are the approximation coefficient and detail coefficient respectively.

The parameter M is a power of 2 which ranges from 0 to J - 1.

Wavelet function has equations described below:

$$\varphi_{j,k}(x) = \sum_{n} \alpha_n \varphi_{\ j+1,n}^{\ j} \qquad (2.4)$$

Where,

$\varphi_{j,k}(x)$ are scaling functions which are actually expansion functions which are composed of integer translation and binary scaling and contained in the set.

The equation above is modified to the equation below:

$$\varphi_x = \sum_n h_{\varphi}(n)\sqrt{2}\emptyset(2x - n) \qquad (2.5)$$

Where, $h_{\varphi}(n)$ are called the wavelet function coefficients. The $h_{\varphi}(n)$ *and can be related to* $h_{\emptyset}(n)$

$$h_{\varphi} = (-1)^n h_{\varphi}(1 - n) \qquad (2.6)$$

An improved watershed algorithm was obtained by incorporating wavelet transform at its post processing stage of the watershed algorithm. This was followed by converting the centre coordinate in watershed transformation to polar coordinate using cart2poly function.

Step1: Get input image….

Step 2: Define the initial wavelet function equation

$$\varphi_{j,k}(x) = \sum_n \alpha_n \varphi_{\substack{j \\ j+1,n}}(x)$$

Where,

$\varphi_{j,k}(x)$ are scaling functions which are actually expansion functions, composed of integer translations and binary scaling contained in the set

Step 3: Get the scaling function expression using the equation below

$$\varphi_{j,k}(x) = 2^{\frac{j}{2}}\varphi(2^j x - k)$$

Step 4: Find the difference between any two adjacent scaling subspaces, Vjand V_{j+1} shown in the equation below:

$$V_{j+1} = V_j \emptyset W_j$$

Step 5: Find the difference between this approximation and the scaling function equation

$$\varphi_x = \sum_n h_\varphi(n)\sqrt{2}\emptyset(2x - n)$$

Where, $h_\varphi(n)$are called the wavelet function coefficients. The$h_\varphi(n)$ *and can be related to* $h_\emptyset(n)$

$$h_\varphi = (-1)^n h_\varphi(1 - n)$$

The discrete wavelet coefficients can be obtained by expanding equation 1

$$W_\emptyset(j_0, k) = \frac{1}{\sqrt{M}}\sum_{x=0}^{M-1} f(x)\varphi_{j0,k}(x)$$

Where,

j ≥ j and the $W_\emptyset(j_0, k)$are the approximation coefficient and detail coefficient respectively.

The parameter M is a power of 2 which ranges from 0 to J - 1.

3. METHODOLOGY

For this work, MATLAB 7.10a was used to design the interface. All other methods adopted for the segmentation approach of improved watershed algorithm were;

3.1 Image Acquisition and Preprocessing

Thirty (30) medical images that were used for the analysis were pre-processed using Gaussian filtering method.

The first step in the pre-processing method was conversion to grayscale as most images obtained were always in colored, which is not suitable for computer analysis. In order to process the images in the MATLAB environment, the images were in grayscale and grayscale involves converting the original RGB image into Black and white for proper processing. The Original image in a RGB form was 3 by 3 matrixes but when converted to RGB, it becomes a 2 by 2 matrix; the third matrix suppressed is the color form. After the conversion, certain physical features of the image still exist except for the indexes (color map) which were removed when it was being converted to grayscale.

The steps involve for the images pre-processing were;

Step 1: Identify image

Step 2: Check if matrix form for image is 3 by 3 matrixes (RGB)

Step 3: Reduce image to 2 by 2 matrixes (gray scale)

Step 4: Check for unwanted particles

Step 5: Gaussian filtering to filter images

Step 6: Stop.

3.2 Improved Watershed Algorithm

Improved watershed was developed by combining wavelet function with existing watershed algorithm. This steps shows the improved algorithm.

Step 1: *Let f: D → N is a digital grey value image, with hmin and hmax the minimum and maximum value of f.*

Step 2: *Let Xh denote the union of the set of basins computed at level h.*

Step 3: *A connected component of the threshold set Th+1 at level h + 1*

Step 4: *Computes the geodesic influence zone of Xh within Th+1*

Step 5: *Update Xh with Xh+1.*

Step 6: *Let Minh denote the union of all regional minima at altitude h.*

Step 7: *Compute* $X_{h+1} = Min_{h+1} \cup IZ_{Th+1}(X_h)$, $h \in [hmin; hmax$

Step 8: *Compute Wshed (f) = D* X_{hmax} *Watershed f is the complement of Xhmax in D*

Step 9: *Define the initial wavelet function equation.*

$$\varphi_{j,k}(x) = \sum_n \alpha_n \varphi_{\substack{j \\ j+1,n}}(x)$$

Step 10: *Get the scaling function expression using the equation below*

$$\varphi_{j,k}(x) = 2^{\frac{j}{2}} \varphi(2^j x - k)$$

Step 11: *Find the difference between any two adjacent scaling subspaces, Vj and* V_{j+1} *shown in the equation below:*

$$V_{j+1} = V_j \emptyset W_j$$

Step 12: *Find the difference between this approximation and the equation*

$$\varphi_x = \sum_n h_\varphi(n)\sqrt{2}\emptyset(2x - n)$$

4. ANALYSIS OF RESULT

In the analysis done, the values of the segmentation accuracy, memory consumed and segmentation time was computed for both the watershed and the wavelet-watershed for thirty (30) medical images. Table 4.1 and table 4.2 highlight the performance results of the wavelet-watershed and the watershed segmentation algorithm for thirty medical images.

Though, it can be observed that improved-watershed algorithm outperformed the existing one in terms of segmentation accuracy, but since accuracy is the most important factor of the three (in medical imaging), it followed that the wavelet-watershed technique still proved better. Table 4.3 shows the Average result of both the wavelet-watershed and watershed algorithm.

Observations clearly revealed that the wavelet-watershed has a higher accuracy, lesser segmentation time and consumed lesser memory than the watershed.

Table 4.1: Results showing the performance of thirty (30) medical images using Existing Watershed Algorithm.

Medical Images	Memory consumption (byte)	Segmentation Time (ms)	Segmentation Accuracy
Image 1	1571880960	39.28316355	8388160
Image 2	1608781824	30.54576722	4138192
Image 3	1635749888	34.69744399	8164784
Image 4	1666785280	43.07312039	8388416
Image 5	1690923008	41.42648107	8377744
Image 6	1707413504	38.55875297	8380544
Image 7	1738067968	45.47604134	7229472
Image 8	1769472000	36.51930095	8211712
Image 9	1794879488	36.41809444	8361872
Image 10	1823715328	33.958728	8388608
Image 11	1279242240	15.5198218	8388160
Image 12	1302011904	17.43348132	4138192
Image 13	1364627456	18.82379753	8164784
Image 14	1379319808	26.15251192	8388416
Image 15	1421344768	21.46789675	8377744
Image 16	1448189952	23.85597134	8380544
Image 17	1470349312	25.48782845	7229472
Image 18	1521397760	33.33514291	8211712
Image 19	1539874816	28.30033192	8361872
Image 20	1563533312	26.02984452	8388608
Image 21	1197998080	4.399886935	8325712
Image 22	1206177792	5.187979317	8388608
Image 23	1234669568	6.565988849	7445104
Image 24	1244508160	6.007681466	8388096
Image 25	1261068288	6.730411044	7673264
Image 26	1274662912	10.99561212	8384512
Image 27	1288306688	11.45005102	8345632
Image 28	1302933504	12.21468078	6838144
Image 29	1314504704	15.66023145	8376048
Image 30	1334005760	15.46262582	8330160

Table 4.3: Results showing the performance of thirty (30) medical images using Wavelet -Watershed Result.

Medical Images	Memory consumption (byte)	Segmentation Time (ms)	Segmentation Accuracy
Image 1	958967808	5.276842795	15530669.25
Image 2	1003741184	8.299816206	7668520.125
Image 3	1031016448	8.466697256	15121281.38
Image 4	1060519936	9.716831745	15531913.5
Image 5	1097252864	10.92934745	15513397.88
Image 6	1146679296	12.86346294	15516508.5
Image 7	1172361216	13.34454557	13339396.88
Image 8	1178501120	18.02678442	15246298.88

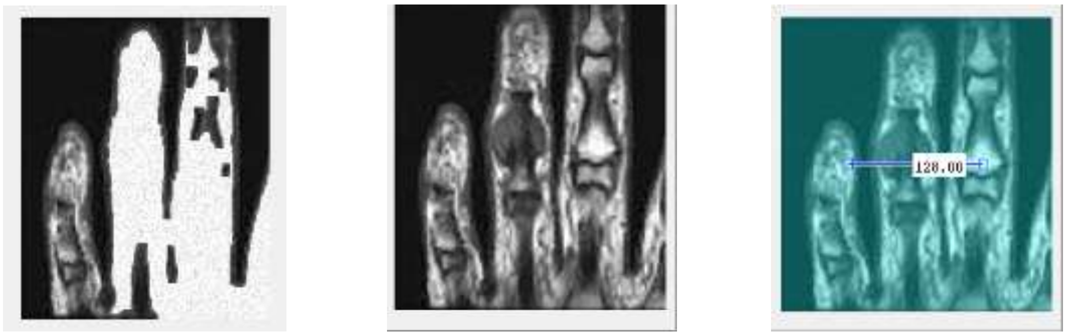
Image 9	1232629760	23.54646596	15483654.38
Image 10	1256525824	19.53557045	15532032
Image 11	1282404352	23.75398869	15530847
Image 12	1320988672	22.72275096	15426241.13
Image 13	1358245888	30.12448824	15530136
Image 14	1380585472	29.90908819	15502910.63
Image 15	1406136320	27.27692747	15195699.38
Image 16	1454211072	26.71658116	12151760.25
Image 17	1472634880	35.97622137	15066978.75
Image 18	1516232704	45.34852037	12248100.75
Image 19	1553977344	43.73045808	15404052
Image 20	1568587776	32.51888316	15360651.38
Image 21	1601814528	47.85790807	15412435.88
Image 22	1631973376	50.64242463	15532032
Image 23	1150857216	5.261245524	13805279.63
Image 24	1180028928	5.955933454	15530373
Image 25	1179123712	5.595263773	14253891
Image 26	1202384896	6.606146883	15520093.13
Image 27	1222557696	10.93671461	15454266.38
Image 28	1227341824	11.03593351	12700237.5
Image 29	1214799872	14.24786464	15505458.38
Image 30	1230954496	14.53600449	15418657.13

Table 4.3: Average result of both the wavelet-watershed and watershed algorithms

	Watershed	**Wavelet-Watershed**
Accuracy	$78.85 * 10^5$	$14.70 * 10^6$
Memory Consumption (byte)	$14.65 * 10^8$	$12.76 * 10^8$
Segmentation Time (ms)	$23.70 * 10^8$	$20.69 * 10^8$

(a) **(b)** **(c)**

Figure 4.1: Samples of segmented images (RBC) (a) Original image (b) Existing Watershed algorithm segmented Image (c) wavelet- watershed algorithm segmented image.



(a) (b) (c)

Figure 4.2: Sample of segmented image (Finger), (a) Original image (b) Existing Watershed algorithm segmented Image (c) wavelet- watershed algorithm segmented image.

5.1 CONCLUSIONS

In this work, existing watershed algorithm for image segmentation was improved by incorporated wavelet algorithm by converting the centre coordinate in a watershed transformation to polar coordinate using cart2poly function which creates an improved watershed algorithm which was used to segment the medical images. The algorithm was implemented using Matlab 7.10a, the performance of the improved watershed was visibly seen in the Segmentation accuracy, Memory consumption and Segmentation time.

In medical operations, time is valuable and everybody wants to minimize resources, but the accuracy of the work done is best of all. Therefore, this work provide improved image segmentation algorithm that has better accuracy, time of completion and memory consumption.

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