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AUTOMATIC PIXEL INTENSITY BASED IMAGE SEGMENTATION USING DWT

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Abstract: Model-Based picture segmentation plays a dominant function in picture evaluation and picture retrieval. To analyze the features of the picture, model based segmentation set of rules could be greater efficient as compared to non-parametric techniques. In this paper, we proposed Automatic Pixel depth Image Segmentation using Wavelets (AISWT) to make segmentation rapid and simpler. The approximation band of photo Discrete Wavelet Transform is considered for segmentation which incorporates vast records of the input image. The Histogram based set of rules is used to achieve the number of regions and the initial parameters like imply, variance and mixing component. The final parameters are received via the use of the Expectation and Maximization algorithm. The segmentation of the approximation coefficients is decided by means of Maximum Likelihood function. It is found that the proposed approach is computationally green permitting the segmentation of huge photos and plays a whole lot advanced to the earlier photo segmentation strategies.

Keywords: Discrete Wavelets, Image Segmentation, Histogram, Generalized Gaussian Distribution, EM Algorithm, ML Estimation.

1. Introduction

In image processing the input is an image and the output is either an image or parameters related to the image is used to solve identification problems, such as forensic medicine or creating weather maps from satellite pictures. Image segmentation is a process of extracting and representing information from an image in order to group pixels together into regions of similarity. Image segmentation is classified into three categories viz., i) *Manual* i.e., supervised or interactive in which the pixels belonging to the same intensity range pointed out manually and segmented, the disadvantage is that it consumes more time if the image is large. ii) *Automatic* i.e., unsupervised which is more complex and algorithms need some priori information such as probability of the objects Having a special distribution to carry out the segmentation.

iii) *Semi-automatic* is the combination of manual and

automatic segmentation**.** The pixel intensity based image segmentation is obtained using Histogram-Based method, Edge-Based method, Region-Based

method and Model-Based method. Model-Based segmentation algorithms are more

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efficient compared to other methods as they are dependent on suitable probability distribution attributed to the pixel intensities in the entire image. To achieve close approximation to the realistic situations, the pixel intensities in each region follow Generalized Gaussian Distribution (GGD). Some of the practical applications of image segmentation are Medical Imaging to locate tumors and other pathologies, locate objects in satellite images viz., roads, forests, etc., automated-recognition system to inspect the electronic assemblies, biometrics, automatic traffic controlling systems, machine vision, separate and track regions appearing in consequent frames of an image sequence and real time mobile robot applications employing vision systems.

Motivation: Image segmentation plays an important role in biometrics as it is the first step in image processing and pattern recognition. Model based algorithms are used for efficient segmentation of images where intensity is the prime feature. The problem of random initialization is overcome by using Histogram based estimation. The Wavelet transform solves the problem of resolution which can indicate the signal without information loss and reduces the complexity. The segmentation is faster since approximation band coefficients of DWT are considered.

Contribution: In this paper, we introduced Wavelet concept for image segmentation which reduces the computation time by considering approximation band of an image which is small in dimensions and contains significant information of original image. The initial parameters and final parameters

are obtained by applying Histogram based algorithm and Expectation and Maximization algorithm respectively. GGD model is constructed and segmented by Maximum Likelihood estimation of each approximation coefficient.

Organization: The rest of the paper is organized into following sections. Section 2 is an overview of related work. Section 3 describes model of AISWT and section 4 discusses the algorithm. Performance analysis of the model is presented in section 5 and conclusion is given in section 6.

2. 2-D Wavelets Transform:

The 1-D DWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. As depicted in Figure 2.1(c), the four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

(a)   (b)   (c)
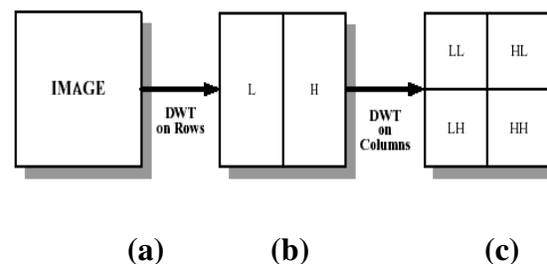
Figure.1. Block Diagram of DWT (a)Original Image   (b) Output image after the 1-D applied on Row input   (c) Output image after the second 1-D applied on row input.
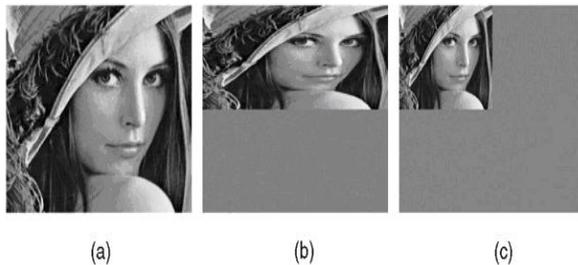
Figure 2. DWT for Lena image (a) original Image (b) Output image after the 1-D applied on column input (c) Output image after the second 1-D applied on row input

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas of Fig. 2.2(b), respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2D-DWT output image is shown in Fig.2.2(c).We can use multiple levels of wavelet transforms to concentrate data energy in the lowest sampled bands. Specifically, the LL sub band in fig 2.1(c) can be transformed again to form LL2, HL2, LH2, and HH2 sub bands, producing a two-level wavelet transform. An (R-1) level wavelet decomposition is associated with R resolution levels numbered from 0 to (R-1), with 0 and (R-1) corresponding to the coarsest and finest resolutions.

The straight forward convolution implementation of 1D-DWT requires a large amount of memory and large computation complexity. An alternative implementation of the 1D-DWT, known as the lifting scheme, provides significant reduction in the memory and the computation complexity. Lifting also allows in-place computation of the wavelet coefficients. Nevertheless, the lifting approach computes the same coefficients as the direct filter-bank convolution. A wavelet transform transforms a signal from the time domain to the joint time-scale domain. This means that the wavelet coefficients are two-dimensional. If we want to compress the transformed signal we have to code not only the coefficient values, but also their position in time. When the signal is an image then the position in time is better expressed as the position in space. After wavelet transforming an image we can represent it using trees because of the subsampling that is performed in the transform. A coefficient in a low subband can be thought of as having four descendants in the next higher subband (see figure1). The four descendants each also have four descendants in the next higher subband and we see a quad-tree emerge: every root has four leafs.
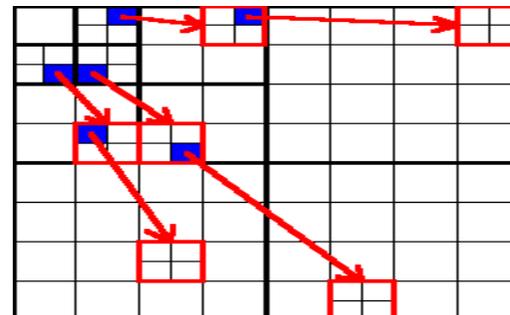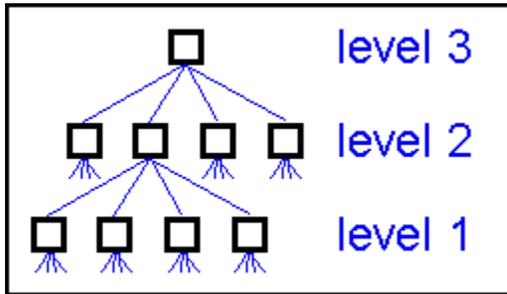
*Figure3:*The relations between wavelet coefficients in different sub bands as quad-trees.

We can now give a definition of the zerotree. A zerotree is a quad-tree of which all nodes are equal to or smaller than the root. The tree is coded with a single symbol and reconstructed by the decoder as a quad-tree filled with zeroes. To clutter this definition we have to add that the root has to be smaller than the threshold against which the wavelet coefficients are currently being measured.

3. Model

In this section we discussed definitions and AISWT model

A**.** Definitions:

i. *Mean*: The average intensity of a region is defined as the *mean* of the pixel intensities within that region.

The mean μz of the intensities over M pixels within a

region K is given by Equation (1)

$$\mu_z = \frac{1}{M}\sum_{i=1}^{M} x_i \quad \text{---------------} (1)$$

Alternatively, we can use formulation based on the

normalized intensity histogram $p(zi)$ where i=0,

1,2,…,L-1 and *L* is the number of possible intensity
values as given by Equation (2)

$$\mu = \sum_{i=1}^{L} z_i p(z_i) \quad \text{---------------} (2)$$

ii. *Variance*: The *variance* of the intensities within a

region K with M pixels is given by Equation (3).

$$\sigma_z^2 = \frac{1}{M}\sum_{i=0}^{M}(x_i - \mu_z)^2 \quad \text{------------} (3)$$

Using histogram formulation the *variance* is given by
Equation (4)

$$\sigma^2 = \sum_{i=0}^{L}(z_i - \mu)^2 p(z_i) \quad \text{---------------} (4)$$

iii. *Probability Distribution Function (PDF) of the*
intensities: The PDF $P(z)$, is the probability that an

intensity chosen from the region is less than or equal to a given intensity value z. As z increases from -∞ to +∞, $P(z)$ increases from 0 to 1. $P(z)$ is monotonic, non-decreasing in z and thus $dP/dz \ge 0$.

iv. *Shaping parameter P*: Shaping parameter defines the peak ness of the distribution which varies from 1 to ∞. The GGD becomes Laplacian Distribution if P = 1, Gaussian Distribution if P=2 and Uniform Distribution if P→ +∞.

v. *Computational Time*: Time required for the

Execution of the algorithm

B. Block diagram of AISWT

The Figure 1 gives the block diagram of AISWT
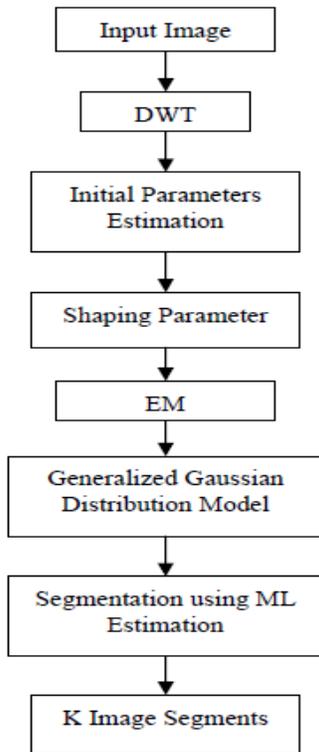
I. *Input image*: The input images are of different formats, sizes and types. The image pixel intensity in the entire image is a Random Variable and follows a GGD.

II. *DWT*: The Wavelet Transform is created by repeatedly filtering the image coefficients on a row by row and column by column basis. A two-dimensional DWT decomposition of image contains various band information such as low-low frequency approximation band, high-low frequency vertical detail band, low-high frequency horizontal detail band and high-high frequency diagonal detail band. We assume

each coefficient of approximation band is a Random Variable z and also follow GGD. The approximation band is used for the segmentation purpose, which is quarter the size and has significant information of the original image. Hence the computation time required reduces.

III. *Initial parameters Estimation*: Initial parameters like *mean* μ, *variance* σ and *mixing parameter* α are

determined using Histogram based initial estimation which is a clustering algorithm. The initial parameters are calculated in two steps

i) Histogram is constructed by dividing approximation band coefficients into intervals and counting the number of elements in each subspace, which is called as bin. The Khighest density bins are selected and the average of the observed elements belonging to the bins is calculated to derive a Centroid. If K centroids are not obtained because of narrow intervals, the Histogram is rebuilt using wider intervals and the centroids are recalculated.

ii) The minimum distance clustering is used to label all the observed elements by calculating the distance D between each centroid and all the elements of the histogram as given in Equation (5)

$$D_j = \min\|C_i - Y_j\| \quad \text{----------------------------- (5)}$$

Where

Ci is ith centroid for i = 1 to K

Dj is minimum distance between Ci and jth element Yj for j = 1 to N

The Histogram based initial estimation do not use random selection for initial parameters, thus the method is stable and

useful for unsupervised image segmentation applications. The obtained mean, variance and mixing parameter for the *k* regions are considered as the initial parameters for EM algorithm.

IV. *Shaping parameter P*: The Shaping parameter defines the peakness of the distribution. In GGD, the three parameters mean, variance and shaping parameter determines the PDF. The optimal shaping parameter is determined using initial parameters and the absolute mean value $E[z]$. The absolute mean is given by Equation (6)

$$E[|z|] = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{k} |z_i - \mu_j| \quad \text{------------ (6)}$$

P is estimated using Equation (7)

$$P = M^{-1}(\rho) \quad \text{------------------------- (7)}$$

Where ρ is given by

$$\rho = \frac{E^2[|z|]}{\sigma^2}$$

M is the Generalized Gaussian ratio function given by Equation (8)

$$M(\rho) = \frac{\Gamma^2\left(\frac{2}{\rho}\right)}{\Gamma\left(\frac{1}{\rho}\right)\Gamma\left(\frac{3}{\rho}\right)} \quad \text{------------------- (8)}$$

V. *Expectation and Maximization*: The EM algorithm is an efficient iterative procedure to compute the ML estimate in the presence of missing or hidden data. For obtaining the EM algorithm a sample of the coefficients

z1, z,..., zn, are drawn with PDF $f(z,\theta)$ given in Equation (15) where θ is set of initial parameters i.e., $\theta = (\alpha, \mu, \sigma 2, P)$.

Each iteration of the EM algorithm consists of two steps as shown in Figure2

i. E-step: It computes the expected complete data Log- Likelihood function $Q(\theta, \theta(i))$ given by Equation (9)

$$Q(\theta, \theta^{(i)}) = \sum_{s=1}^{N} \sum_{t=1}^{K} \left[\log\left(\alpha_t f\left(z_s, \theta_t^{(i)}\right)\right)\right] t_t\left(z_s, \theta^{(i)}\right)$$

$$\text{------------ (9)}$$

Where $t_t(z_s, \theta^{(n)})$ is a Posterior Probability and is given
by Equation (10)

$$t_t(z_s, \theta^{(i)}) = \frac{\alpha_t^{(i)} f\left(z_s, \theta_t^{(i)}\right)}{h\left(z_s, \theta^{(i)}\right)} \quad \text{------------ (10)}$$

$$h(z_s, \theta^{(i)}) = \sum_{t=1}^{K} \alpha_t f\left(z_s, \theta_t^{(i)}\right) \quad \text{--- (11)}$$

ii. M-step: It finds the (i+1)th estimation θ (*i*+1) by updating *mixing parameter, mean* and *variance* using Equations (12), (13) and (14) respectively to maximize Log-Likelihood function $Q(\theta, \theta^{(i)})$

$$\alpha_t^{(i+1)} = \frac{1}{N} \sum_{s=1}^{N} t_t\left(z_s, \theta^{(i)}\right) \quad \text{--------------- (12)}$$

$$\mu_t^{(i+1)} = \frac{\sum_{s=1}^{N} t_t\left(z_s, \theta^{(i)}\right) z_s}{\sum_{s=1}^{N} t_t\left(z_s, \theta^{(i)}\right)} \quad \text{------------ (13)}$$

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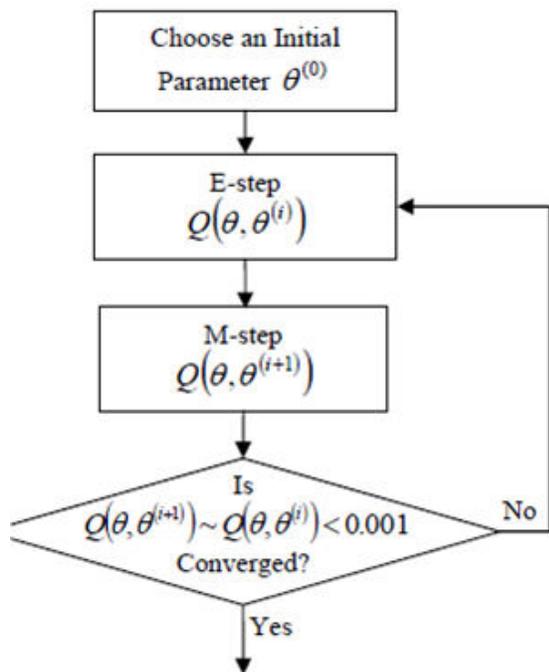
Fig.4: Flow chart of EM algorithm

$$\sigma_t^{(i+1)} = \left[\frac{\sum_{s=1}^{N} t_t\left(z_s, \theta^{(i)}\right)\left(\frac{\Gamma(3/P)}{P\Gamma(1/P)}\right)\left\|z_s - \mu_t^{(i)}\right\|^{\frac{1}{P}}}{\sum_{s=1}^{N} t_t\left(z_s, \theta^{(i)}\right)} \right]^{\frac{1}{P}}$$

----- (14)

The EM algorithm will converge when the difference of the old estimates and the new estimates is less than the threshold value 0.001. The EM algorithm used for estimating the final parameters is heavily dependent on number of segments and the initial parameters of the model.

VI. *Generalized Gaussian Distribution model*: The GGD model is obtained using the final parameters. The approximation band coefficients of each image region follow a particular distribution such as

Gaussian, Laplacian, Uniform etc., and characterize the GGD Model with shaping parameter *P*. The PDF is given by Equation (15)

$$f(z,\theta) = \frac{1}{2\Gamma\left(1+\frac{1}{P}\right)A(P,\sigma)} e^{\frac{\left|(z_s-\mu_t)\right|^P}{|A(P,\sigma)|}} \quad --- (15)$$

Where,
s=1 to N and i=1 to K

$$\text{for } \sigma > 0, \quad A(P,\sigma) = \left[\frac{\sigma^2 \Gamma\left(\frac{1}{P}\right)}{\Gamma\left(\frac{3}{P}\right)} \right]^{\frac{1}{2}}$$

The function $A(P,\sigma)$ is a scaling factor and *P* is the
shape parameter. The GGD becomes Laplacian
Distribution if $P = 1$, Gaussian Distribution if $P = 2$ and Uniform Distribution if $P \rightarrow +\infty$.

VII. *Segmentation using Maximum Likelihood Estimation*: The segmentation is carried out by assigning each coefficient into proper cluster according to the ML estimation given by Equation (16)

$$L = \max_t \{f(z_s, \theta_t)\} \quad ------------------ (16)$$

VIII. *K image segments*: The *K* segmented regions are obtained and for K=2, the image is segmented into foreground and background. The pixel intensities of segmented region obtained follow a corresponding GGD.

4. Algorithm

Problem definition:

Consider an image, the objectives are to

i. Segment the given image using DWT.

ii. Initial parameters are obtained using Histogram and EM

iii. Segmentation is done using ML Estimation

Assumption: Each coefficient of approximation band is a Random Variable z and also follows GGD

Table 1 gives the AISWT Segmentation algorithm in

which approximation band of image DWT is used to

estimate parameters which are required for segmentation.

• Input : Image of variable size

• Output : Segmented regions

1 DWT is applied on an image and approximation band is considered.

2 Histogram Based method is applied to obtain initial parameters like *mean*, *variance* and *mixing parameter*

3 Shaping parameter P is determined

4 Expectation and Maximization algorithm is used to get updated final parameters.

5 PDF of Generalized Gaussian Distribution is determined

6 Segmentation is obtained using Maximum-Likelihood estimation

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Table1: Algorithm of the AISWT

5. Performance Analysis

Images Rose flower, Flower, Starfish and Boat of sizes 150*94, 127*127, 800*600 and 800*603 respectively are considered for performance analysis. If the number of segments are selected as two i.e., K=2 foreground and background can be differentiated in an image. Figures 3, 4, 5 and 6 gives the segmentation results of Sea, Flower, Starfish and Boat in which the original image, mask, segment 1 and segment 2 are shown in Figures a, b, c and d respectively. Table 2 gives the comparison of computational time between FGM, FGGD and AISWT. It is observed that as dimension of the image increases, the computational time increases. The existing algorithms FGM and FGGD require more time compared to the proposed algorithm AISWT. AISWT requires 30% less time compared to FGM and 70% less time compared to FGGD. Table 2: Comparison of Computational time for FGM, FGGD and AISWT

Table2 : Comparison of Computational Time

Images	FGM	FGGD	AISWT
Rose	2.36	1.48	0.3628
Flower	4.67	2.87	0.3688
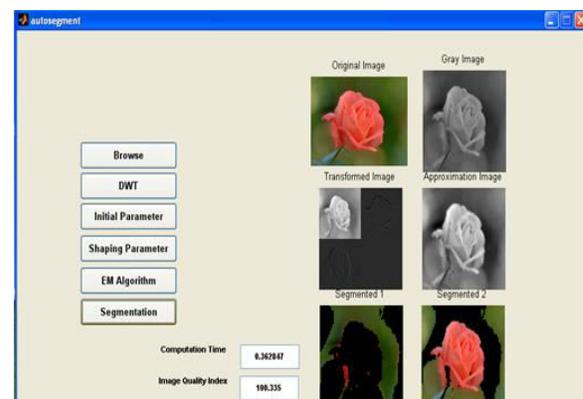
Fig 5: a) Original Rose flower (150*94) b) Mask c) Segment 1 d) Segment 2

Table 3: Comparison of Image Quality Index for FGM, FGGD and AISWT

Images	FGM	FGGD	AISWT
Rose	68	75	100
Flower	55	62	96

Table3: Comparison of Image quality Index
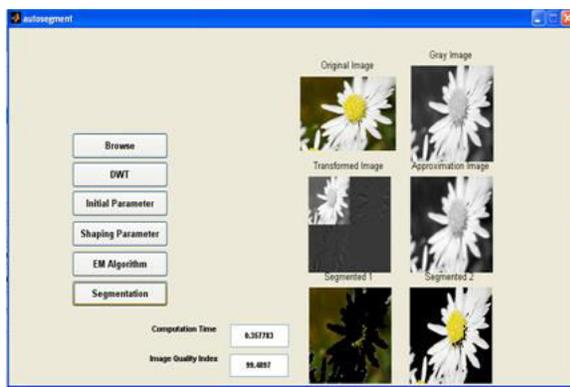
Fig 6 a) original Flower (127*127) b) mask
c) Segment 1 d) Segment 2

Table 3 gives the comparison of Image quality Index
between FGM, FGGD and AISWT. It is observed that proposed model AISWT has higher Image Quality Index compared to existing algorithms FGM and FGGD.
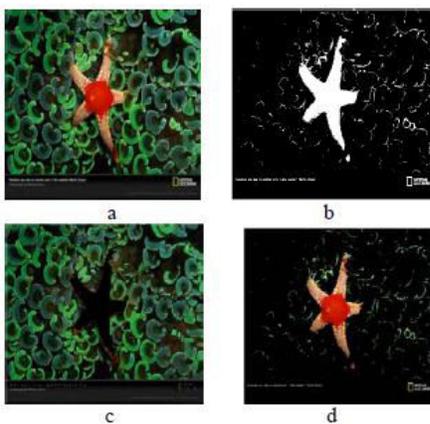
Fig 7 a) original Starfish (800*600) b) Mask c) Segment 1 d) Segment 2
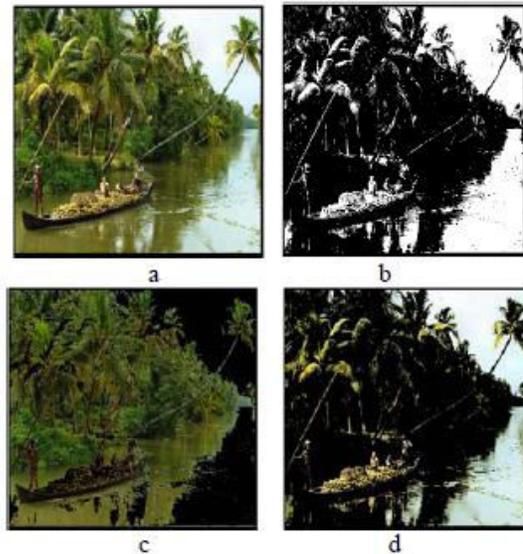
Fig 8 a) Original Boat (800*603) b) Mask c) Segment 1 d) Segment 2

6. Conclusion

In this paper, we proposed fast segmentation algorithm AISWT. The approximation band of an image DWT is considered as a mixture of K-Component GGD. The initial parameters are estimated using Histogram based method. Through EM algorithm, the final parameters are obtained. The segmentation is done by ML estimation. The AISWT algorithm is computationally efficient for segmentation of large images and performs much superior to the earlier image segmentation methods FGM and FGGD in terms of computation time and image quality index.

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