A MULTILEVEL AUTOMATIC THRESHOLDING FOR IMAGE SEGMENTATION USING GENETIC ALGORITHM AND DWT

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Abstract – In this paper, An Automatic Multilevel Thresholding Method for Image segmentation is proposed based on Discrete Wavelet Transforms and Genetic Algorithm. We have combined Genetic Algorithm with DWT to make Segmentation faster and adequate results. First the length of the histogram is reduced by using DWT. Using this Reduced Histogram, the number of Thresholds and Threshold Value are determined by Genetic Algorithm. The Thresholds are then projected in original Space. From the analysis of results, it can be concluded that the proposed method is fast and accurate.

Keywords -Histogram, Thresholding, Genetic Algorithm, Discrete Wavelet Transform

I. INTRODUCTION

Image segmentation, using one or more operations to divide image into number of similar regions is the basic technique of image processing and important component of image analysis and vision system. 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.

All the subsequent tasks, including feature extraction, model matching and object recognition rely heavily on the quality of the image segmentation process. Thresholding is undoubtedly one of the most popular segmentation approaches for the sake of its simplicity. It is based on the assumption that the objects can be distinguished by their gray levels. Thresholding involves bi-level thresholding and multilevel thresholding. Bi-level thresholding classifies the pixels into two groups, one including those pixels with gray levels above a certain threshold, the other including the rest. Multilevel thresholding divides the pixels into several classes. The pixels belonging to the same class have gray levels within a specific range defined by several thresholds. Both bi-level and multilevel thresholding methods can be classified into parametric and non-parametric approaches. The non-parametric approach is based on a search of the thresholds optimizing an objective function, such as the between-class variance (Otsu's function)[1]. In the parametric approach, the gray level distribution of each class has a probability density function that is assumed to obey a given distribution. A great number of thresholding methods of parametric or non-parametric type have been proposed in order to perform bi-level thresholding [2]. They are extendable to multilevel thresholding as well. However, the amount of thresholding computation significantly increases with this extension. To overcome this problem, several techniques have been proposed.

In [3], the Otsu's function is modified to optimize by a fast recursive algorithm along with a look up table. In [4], Lin has proposed a fast thresholding computation using the Otsu's function. In [5], the resolution of the histogram is reduced using the wavelet transform. The fast multilevel thresholding technique has been proposed by Yin [6]. The thresholds optimizing the Otsu's or the Kapur's function is searching by using an iterative scheme.

Several techniques using genetic algorithm have also been proposed to solve the multilevel thresholding problem [7-13]. GAs are the optimization algorithms based on the mechanics of natural selection and natural genetics. Yin [7] has proposed a fast thresholding method based on a genetic algorithm where the objective function is similar to Otsu's and kapur's function. Tao et al. use a genetic algorithm in order to find the optimal combination of the fuzzy parameter by the maximizing the fuzzy entropy [12].

The main problem associated with above methods is that the no. of thresholds for segmenting the image cannot be automatically determined. To overcome this problem Yen et al. Proposed a new criterion for multilevel thresholding called Automatic Thresholding Criterion (ATC) [14]. This criterion is used with sequential dichotomization technique [15]. In [16], the dichotomization process is repeated until a cost function derived from Otsu's function becomes higher than a specific value. The dichotomization techniques are faster algorithms, but they are sub-optimal techniques, they do not providing the optimal threshold values.

In this paper the authors present techniques of automatic multilevel thresholding using genetic algorithm and DWT by optimizing Automatic Thresholding Criterion (ATC). The proposed GA uses a new string representation of the chromosome. It is combined with a wavelet transform based technique in order to reduce the time computation. The using of GAs has many advantages over traditional searching techniques [17]. Particularly, GA-based methods are global searching techniques capable, most often, to prevent from trapping into locally optimal solutions. Another advantage is that the GA-based methods can become faster through parallel implementations. In the next section, the proposed multilevel thresholding technique using a GA is described.

In section 2, the automatic thresholding criterion is explained. In Section 3, the performance of the proposed method is tested on several examples Section 4. Concluding remarks are given in Section 5.

II. AUTOMATIC THRESHOLDING CRITERION

It is well-known that the thresholded image becomes more similar to the original one as the classification number increases. Hence, the discrepancy between the original and thresholded images decreases as the classification number increases. However, the total number of bits required to represent the thresholded image increases as the number of classes increases. Hence, there must exist a compromise between these two factors.

Let P_i , m_i and P be the probability of the class C_i, the mean gray level of the class C_i and the total mean gray level of the image, respectively:

$$\boldsymbol{P_i = \sum_{j=t_{i-1}}^{t_{i-1}} P_j\,,\ m_i = \frac{\sigma_i}{P_i}, \sigma_i = \sum_{j=t_{i-1}}^{t_{i-1}} P_j,\ m = \sum_{j=0}^{L^r-1} jP_j,} \quad \textbf{(1)}$$

Where $P_i = \mathrm{h^r(j)/N}$ is the normalized probability at level j.

Using above equations we can evaluate within-class variance σ_w^2, the between-class variance σ_B^2 and the total class variance σ_T^2, the expressions are written here.

$$\sigma_w^2(k) = \sum_{i=0}^{k-1}\sum_{i=t_i}^{t_{i+1}-1}(j - m_{i+1})^2 P_j\,, \sigma_B^2(k) = \sum_{i=1}^{k} \mathrm{P_i(m_i - m)^2},\ \sigma_T^2(k) = \sum_{i=0}^{L^r-1}\mathrm{(j - m)^2\ P_j.} \quad (2)$$

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Cost function for image

$$F(k) = \rho * (Disk(k))^{1/2} + (log_2(k))^2 \quad (3)$$

Here Disk (k) represents the within-class variance,

$$\boldsymbol{Disk(k) = \sigma_w^2(k) = \sigma_T^2 - \sigma_B^2(k)} \quad (4)$$

The first term of F(k) measures the cost incurred by the discrepancy between the thresholded image and the original image. The second term measures the cost resulted from the number of bits used to represent the thresholded image. In this equation, ρ is a positive weighting constant.

III. AUTOMATIC MULTILEVEL THRESHOLDING METHOD

An image is a two dimensional function *f(x, y)*, where *(x, y)* are spatial co-ordinates and the amplitude of *f at* any pair of coordinates *(x, y)* is called intensity or gray level of the image at that point. A digital image is a representation of a two-dimensional image as a finite set of digital values called picture elements or pixels. A pixel may be simply a bit or a much larger data structure. Pixel values typically represent gray levels, colors, etc [19].

If an image *I* having N pixels with L gray levels L = {0, 1, ..., L-1}, it can be classified into k classes (C_1, C_2, ..., C_k) with the set of thresholds T = {t_1, t_2, .. ., t_{k-1}}. The proposed genetic thresholding technique is based on a standard GA. It allows the determination of the number of thresholds as well as appropriate threshold values. Main steps of this method are summarized in algorithm.

Algorithm: Main steps of the proposed automatic multilevel thresholding techniques

1. Compute the histogram of given image
2. Reduce the length of the histogram
3. Generate an initial population
4. Store the best string with the best fitness in a separate location(Tournament selection)
5. Generate the next population after performing the selection, crossover and mutation operations.
6. Compare the best string of the current population with best string of step 4. If new has a better fitness value than previous one, then replace previous by new.
7. Go to step 3 if the desired number of generations is not reached.
8. Expand the best thresholds.

1) REDUCTION OF HISTOGRAM LENGTH

The length of histogram must be reduced in order to accelerate the convergence of GA. The histogram can be reduced using wavelet [6], because a wavelet is a localized function that can be used to captive information, efficient & useful

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description of a signal. The original histogram can be decomposed in two types of signals. First signal is a trend signal; other signal is the detail signal. Trend signal contains the maximum characteristic of the original histogram.

We divide the original signal (image) into frequency resolution and time resolution contents. For this purpose, a cutting window will be used. This window is known as "Mother Wavelet". The problem here is that cutting the signal corresponds to a convolution between the signal and the cutting window. The signal will convolve with the specified filter coefficients and gives the required frequency information. The traditional DWT can be realized by convolution-based implementation. In the forward transform, the input sequences are down sampled and filtered by low-pass filter and high-pass filter to obtain the low-pass (equation 1) and high-pass (equation 2) DWT coefficients. The equations may be written as follows: [5]

$$s[n] = \sum_k h[k]x[2n-k]\,,\, d[n] = \sum_k g[k]x[2n-k] \qquad (5)$$

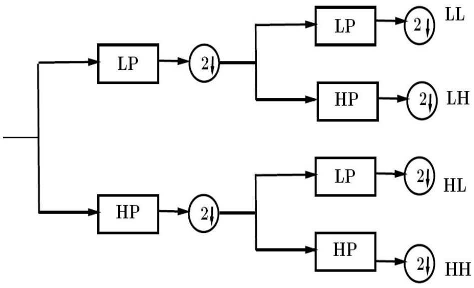


Figure 1 Sub band Decomposition of image

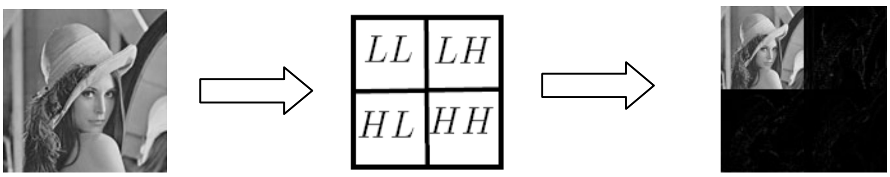


Figure 2 Decomposition of Lena Image 128x128

The wavelet transform at a level r is performed with decimation operation by 2^r after the convolution of the histogram.

$$h^r(j) = WT^r[h(i)], \quad r \in h^r(j) + h_w^r(j) \qquad (6)$$

Where $h^r(j)$ is the trend of the original histogram and $h_w^r(j)$ is the detailed of the original histogram at the r^{th} level. Each trend signal can be reduced dimension signals at level r+1. For a level r, the length of the reduced histogram is denoted by L^r such that $L^r = L/2^r$.

2) STRING REPRESENTATION

In this method, the chromosome is encoded as a binary string of the same size L^r of the reduced histogram, such that A = $a_0, a_1, a_2, \ldots . a_{L-1}^r$, where the character a_i is equal to 0 or 1. a_i indicates the peak or valley of the histogram. If a_i=0 the position i indicates the value of the threshold. Hence number of zeros-bits occurred in A indicates number of thresholds.

3) FITNESS COMPUTATION

The fitness of a string is computed using the cost function ACT proposed by Yen et al. [16]. The fitness F(k) has defined as cost function in section 2. The (k-1) number of thresholds is determined by counting the number of zero-bits in the string and the threshold values are determined by the positions occupied by these zero-bits in the string. The function F(k) has a unique minimum, which is an important advantage. The optimum class number k* and the (k*-1) best thresholds can be determined by the following equation:

$$F(k^*) = \min\{F(k)\} \qquad (7)$$

4) POPULATION INITIALIZATION

The genetic algorithm starts with a randomly generated population of solutions. The initial population is of fixed size P: $A_1, A_2 \ldots A_P$. For each string i in the population (i=1, 2, . . ., P), L^r bits (0 or 1) are randomly generated.

5) GENETIC OPERATIONS

The current population evolves to the next population of the same size using three standard genetic operations: selection, crossover and mutation. The evolution process is iterated until a specified number of generations is reached.

a) SELECTION

Selection is a process which mimics the natural survival of the fittest creatures. Each string has a fitness value obtained by evaluating the fitness function. The probability of each string to be selected is proportional to its fitness value. In this paper, the tournament selection procedure is performed as follows: two strings A' and A" of the current population are randomly selected and the string with the best fitness value is chosen to belong to the mating pool. This procedure is repeated, until filling a mating pool of the same size P that the population.

b) CROSSOVER

The crossover operator chooses two strings A' and A" of the current population. Single crossover is applied as follows: generate a random integer number q within $[0, L^r-1]$ and create two offspring by swapping all the characters of A' and A" after position q. The crossover is performed with the crossover probability P_c. A random number can be generated within [0, 1], associated with each pair of strings selected in the mating pool. If the random value is less than P_c, then the crossover is performed, otherwise no crossover is performed.

c) MUTATION

Mutation is an occasional alteration of a character with a low probability P_m. The proposed mutation is performed in two steps. First, a standard mutation is used in the following way: for each string produced by crossover operation, a random value is generated within [0, 1]. If the random number is less than P_m, then a character at a random position is chosen and its value is altered (i.e. one changes 0 to 1, or 1 to 0).

However, the crossover and standard mutation operators can create strings with several successive zero-bits. In this situation, several thresholds with successive values appear. To overcome this undesirable situation, a solution consists in keeping, among successive zero-bits, only the first one, and in mutating the remaining successive zero-bits.

6) EXPANSION OF THE BEST THRESHODS

Because of the reduced dimension of the histogram, the threshold values t_i determined by the GA are at lower level, i.e. $t_i \in [0\ L]$. Thus, the thresholds determined by the GA must be expanded in the original space. In this case, each threshold t_i is multiplied by a factor 2^r, as follows [5]:

$\hat{t}_i = t_i 2^r$, for i=1, ... , k-1, such that $\hat{t}_i \in [0\ \ L]$

IV. RESULTS

We have done experiments on standard gray images. We add an artificial histogram in order to objectively show the accuracy of the proposed approach in the determination of the appropriate number of the thresholds and the combination of threshold values. The artificial histogram is constructed with k=4 distributions fig 3. Each distribution is assumed to be Gaussian.

The proposed multilevel thresholding technique using a GA is implemented with the following parameters: P_c=.9, P_m=.0001. The size P of population depends on the chromosomes and on the resolution level r=2 used in the wavelet transform. In all our experiments, P is 70 and the GA is executed for a maximum of 50 generations. The wavelet transform is performed with 'coiflet' wavelet. Additional results are presented in order to investigate the influence of the resolution level r. The choice of the constant ρ in objective function is very crucial [16]. After several simulations using different images, we have found that ρ can be taken with relation 0.5×2^r. This relation is the result of our interest creating the relation with resolution level.

For the artificial histogram, the proposed multilevel thresholding technique using a GA with P=70 and iteration=50 converges to k*=4, with the three thresholds T*= (22-34-48) in the reduced range from 0 to 64. The corresponding thresholds are displayed in Figure 3. The results of proposed method are consistent with the number of classes in the artificial histogram and the corresponding threshold values are located on the valleys of the histogram.

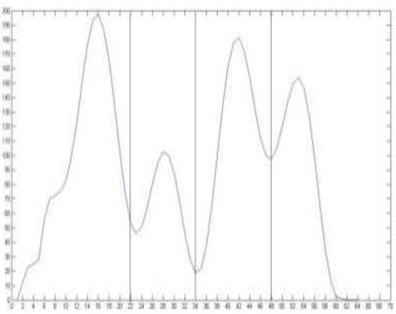
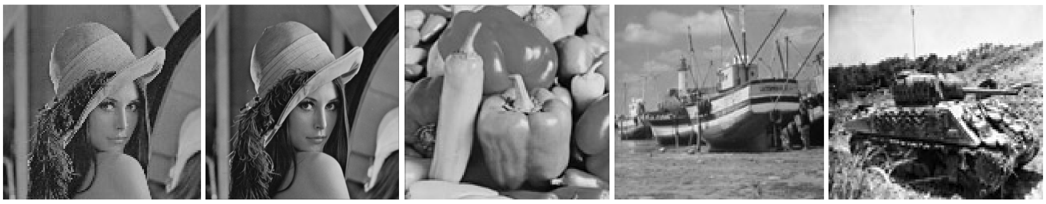


Figure 3: Artificial histogram with thresholds 22-34-48

Table 1: Thresholds for gray images by proposed method

Images	Thresholding values	Number of thresholds
Lena 128*128	56,96,119,164	4

Lena 512*512	84,132,152,188	4
Pepper 128*128	36,92,144,192	4
Boat 128*128	80,132,196	3
Tank 128*97	60,132,184	3



(a) (b) (c) (d) (e)

Figure 4: Original images (a) lena 128*128, (b) lena 512*512, (c) pepper 128*128 , (d) boat 128*128, (e) tank 128*97

(a) (b) (c) (d) (e)

Figure 5: Segmented Images (a) lena128*128, (b) lena 512*512, (c) pepper 128*128, (d) boat 128*128, (e) tank 128*97

Original images and the corresponding segmented images are displayed in figure 4 & 5. Almost all important components are preserved in the thresholded images, since the homogeneous regions are well apparent and their outlines are very clear.

V. CONCLUSION

In this paper, we proposed a new Automatic Multilevel Thresholding Method for Image segmentation is proposed based on Discrete Wavelet Transforms and Genetic Algorithm, which enables determining the appropriate number of thresholds, as well as the adequate threshold value. The length of original histogram is reduced using DWT. The optimal threshold values are determined by using a standard GA. In this GA is used a new string representation of the chromosome, which is different from current representations. Experiments with a synthetic histogram and real images have proved the robustness of the proposed method.

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