Genetic Algorithm and DWT Based Multilevel Automatic Thresholding Approach for Vehicle Extraction

Rakesh Kumar, Tapesh Parashar, Gopal Verma

Abstract - Vehicle Extraction from aerial images is an important research topic in surveillance, traffic monitoring and military applications. In this paper, an approach based on Automatic Multilevel Thresholding has been proposed for extracting vehicles from aerial imagery. The approach combines Genetic Algorithm with DWT to make segmentation faster and geometric feature of vehicles for vehicle extraction. This algorithm analyses the color and connected properties of pixels to extract the outline of vehicles. In this research, UAV colour imagery is examined experimentally. After analysis, it is examined that proposed method provides the vehicle position accurately.

Keywords - Histogram, Thresholding, Genetic Algorithm, Discrete Wavelet Transform, Morphological Processes, Edge Detection, Aerial Imagery

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.

In Automatic Traffic Controlling System, the usefulness of system is dependent on accurately estimating the traffic flow conditions on traffic networks being monitored and managed. In ground based data, cameras at fixed locations for traffic monitoring cannot easily observe the spatial locations and movement of traffic beyond the field of view. Due to the spatial scale and connectivity [1], airborne based data have the potential to significantly enhance the quality of traffic conditions estimations. Zhao and Nevatia [2] explore a car recognition method from low resolution aerial images.

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Hinz [3] discusses a vehicle detection system which attempts to match vehicles against a 3D-wireframe model in an adaptive top-down manner. Kim and Malik [4] introduce a faster 3D-model based detection using a probabilistic line feature grouping to increase performance and detection speed.

Vehicle Extraction described in this paper uses automatic multilevel thresholding method, which optimizes Automatic Thresholding Criterion (ATC) [5] with genetic algorithm and DWT. 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 [8]. 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.

Firstly, three RGB histograms calculated separately. Then we have applied automatic multilevel thresholding on these three histograms. After evaluating all three thresholded histogram, we have merged these histograms again in three dimensional space. Secondly, the post-processing procedure is carried out on segmented image by using mathematical morphological operators to extract the outlines of vehicles.

In section II, the automatic thresholding criterion is explained. In Section III, the performance of the proposed method is tested on several examples Section IV. Concluding remarks are given in Section V.

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 m 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:

$\mathbf{P_i} = \sum_{\mathbf{j=t_{i-1}}}^{\mathbf{t_{i-1}}} \mathbf{P_j}\,, \mathbf{m_i} = \frac{\boldsymbol{\sigma}_\mathbf{i}}{\mathbf{P_i}}, \boldsymbol{\sigma}_\mathbf{i} = \sum_{\mathbf{j=t_{i-1}}}^{\mathbf{t_{i-1}}} \mathbf{P_j},\ \mathbf{m} = \sum_{\mathbf{j=0}}^{\mathbf{L^r-1}} \mathbf{jP_j},$

Where $P_i = h^r(j)/N$ 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.

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

Cost function for image

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

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

$$\mathbf{Disk(k)} = \boldsymbol{\sigma}_\mathbf{w}^\mathbf{2}\mathbf{(k)} = \boldsymbol{\sigma}_\mathbf{T}^\mathbf{2} - \boldsymbol{\sigma}_\mathbf{B}^\mathbf{2}\mathbf{(k)}$$

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. DESCRIPTION OF PROPOSED APPROACH

A. 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 [9].

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. Figure 1 represents the flow chart of the complete algorithm.

Algorithm: Main steps of the proposed Vehicle Extraction Technique

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.
9. Evaluate the binary in segmented image.
10. Apply binary morphological filters in search of vehicle geometry.

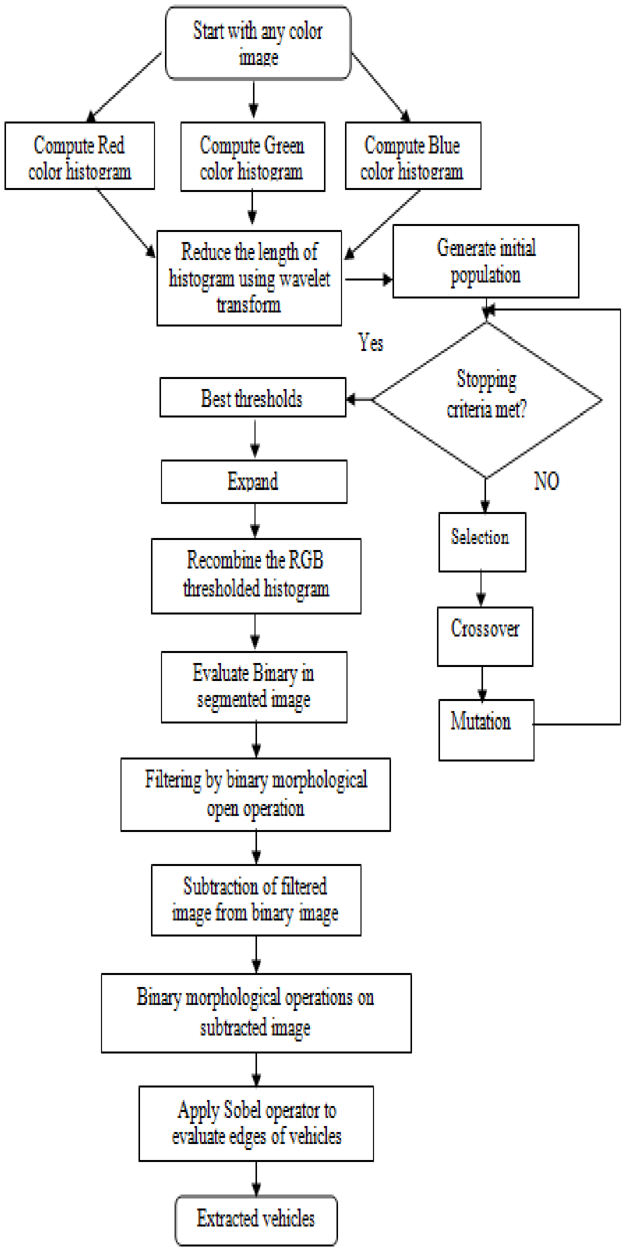

Figure 1: Flow Chart

11.	Apply sobel operation to delineation of vehicle outline.

a. Separate RGB Histograms

Three N-bin histograms are calculated. Each colour component is considered separately, resulting in three colour histograms. This way the combination of the components of a colour is lost. However, the size of the histograms is very small with the total number of bins equals 3N.

b. 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 and useful 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:

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

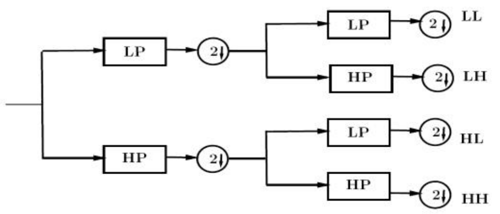

Figure 2: Subband Decomposition of Image

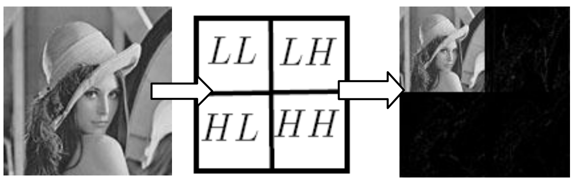

Figure 3: Decomposition of Lena Image

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

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

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 $L^r = L/2^r$.

c. 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 $A=a_0, a_1, a_2, \dots, a^r_{L-1}$, 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.

d. 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:

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

e. Population Initialization

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

f. 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.

i. 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.

ii. 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.

iii. Mutation

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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.

g. Expansion of the Best Thresholds

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 [6]:

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

B. Vehicle Extraction

After the segmented images are obtained by the above multilevel thresholding method, the binary object image can be extracted by selecting the pseudo-color corresponding to the object regions [10]. The vehicles in the binary image are corrupted by noise objects, which have the similar color to objects. To make vehicle regions clear, we applied binary morphological operations to filter the corrupted image. The appropriate combinations of binary dilation, erosion, opening, and closing should be chosen according the noise objects.

C. Delineation of Vehicle Outline

To extract the vehicles according to the color features of the vehicles and uses an edge extraction algorithm to detect the skeletons of the detected buildings. The edges of the extracted vehicles are delineated using the sobel operators [9].

IV. RESULTS

We have done experiments on UAV aerial image. 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. 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.

We have calculated three RGB histograms. Each color component is considered separately, resulting in three color histograms. Then we have applied our algorithm on these three histograms. After evaluating all three thresholded histogram, we have merged these histograms again in three dimensional space. Figure 4(b) shows the segmented image for original image. Table 1 shows threshold values for all three images and for their three color histograms.

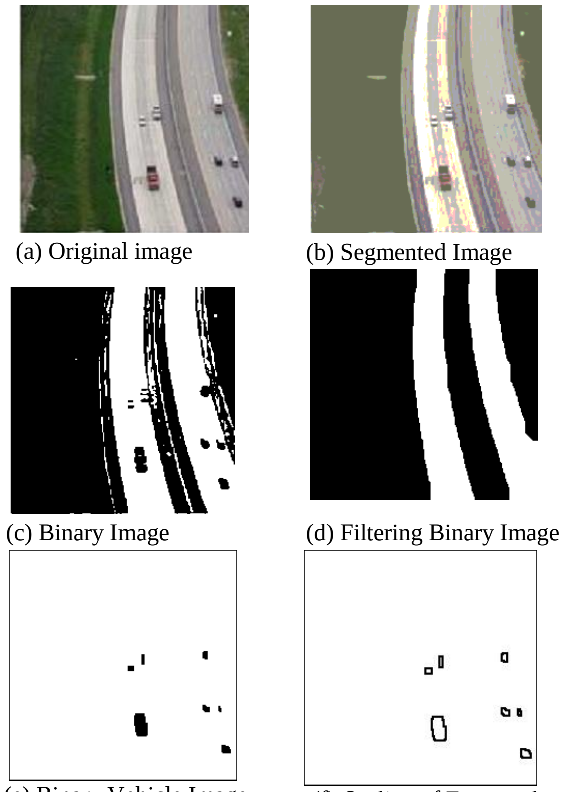
Almost all important components are preserved in the thresholded images, since the homogeneous regions are well apparent and their outlines are very clear.

Images	Thresholding Values		
	Red	Green	Blue
Lena	92-152-192-216	80-140-196	76-112-172
Traffic	98-112-170-186	76-144-184-210	72-102-148
Traffic-2	104-124-164-192	108-124-164-192	84-104-136-176-196

Table 1: RGB thresholds for color image by proposed method

In the vehicle extraction approach, we try to use the uniform radiations from road. The road cluster is selected and the vehicle in the segmented imagery can be seen as "noisy". Figure 4(c) shows the binary image.

Binary image is filtered by binary morphological open operation, to extract the solid road from figure 4(d). The binary morphological operations are carried on the vehicle to obtain complete vehicle as shown in figure 4(e). The edge of the extracted vehicles is delineated using the sobel operations and the result is shown in figure 4(f).



(a) Original image (b) Segmented Image

(c) Binary Image (d) Filtering Binary Image

(e) Binary Vehicle Image (f) Outline of Extracted Vehicle

Figure 4: Set of Images

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V. CONCLUSION

In this paper, histogram-based method is used for image segmentation. To extract the vehicles from UAV aerial imagery, we use the uniform radiation of the roads and geometric feature of vehicles. This pre-processing approach combines Discrete Wavelet Transforms and Genetic Algorithm. The post-processing procedures provide proper outlines of the vehicles. The analysis of experiments shows the applicability of the proposed method. The information can be used for vehicle classifications and traffic flow computation.

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