An Analysis on Road Extraction from Satellite Image Using Otsu Method and Genetic Algorithm Techniques

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Abstract:- Image segmentation is extensively used in face recognition, fingerprint matching, medical image processing and image processing applications, particularly to locate objects in the satellite images. Road extraction from satellite or aerial imagery is a popular topic in remote sensing, and there are many road extraction algorithms suggested by various researches. However, the need of reliable remotely sensed road information still persists as there is no sufficiently robust road extraction algorithm yet. This paper presents a road extraction problem based on Otsu Thresholding and Genetic Algorithm based segmentation. The empirical evaluation of the two algorithms suggests that the GA algorithm is capable of extracting majority of the road network, and it poses promising performance results.

Key-words:- Otsu Thresholding Segmentation, Genetic Algorithm, Road Extraction, Morphological operations

1 Introduction

Automatic detection and delineation of roads from aerial and satellite images has gained an increasing attention in digital photogrammetry and computer vision. Research differs in the type and resolution of input images, the primitives employed for road identification, experiment configurations, way of processing, general assumptions, and so on. All of these things contributed to a vast number of techniques. The major problem to be overcome in this context is the complex structure of the images which contain several different objects such as roads, houses, trees etc. with differences in spectral and geometrical properties. In order to appropriately detect roads from the whole image, the visual characteristics of roads should properly be modeled. An imaged object is defined and identified by its characteristics, which can be classified in five groups: photometric, geometric, topological, functional and contextual. Examples of these characteristics for an imaged road are:

- Road surface usually is homogeneous, at least in a certain portion of the image (photometric);
- Road surface often has a good contrast to its adjacent areas (photometric);
- Roads are elongated (geometric);
- Roads have a maximum curvature (geometric);
- Roads do no e nd without a reason(topological);
- Roads intersect and form a n etwork (topological);
- Roads are means of communication between locations(functional);
- Roads may be indicated by a special distribution of trees (contextual);

These characteristics describe many features that are used by a human operator to recognize roads in an image. Especially the functional and contextual characteristics require intelligence in order to exploit them in the image interpretation process. In practice, the prevalent road properties used in local tests are the spectrum of road materials such as concrete and asphalt, intensity edges at road sides, and the road surface intensity profile. These photometric properties are combined with the road shape constraints, geometric properties in road finding, tracking and linking procedures.

In order to compare the performance of segmentation techniques in road extraction, the following goals have been chosen:

1. Acquisition of initial GIS information and image preprocessing.
2. Automatic road network detection by means of segmentation based on thresholding and genetic algorithm.

3. Geometrical definition of road network based on morphological operations.
4. Evaluation and validation.

Existing Methods

A new object based road extraction strategy suitable for large scale image maps is elaborated in the paper [1]. The road extraction model is composed of two parallel processes; first one aims to detect straight line segments and the second process is responsible for finding road skeleton. An automatic road detection approach is studied by based on edge detection and tracing strategy [17]. The proposed algorithm first preprocesses the input image to reduce noise and adjust contrast in order to ease the separation of road objects from the background. The authors presume the intensity distributions of road regions as being distinguishable from image histogram, and raw road mask is attained by using Otsu thresholding applied on the gray scale image. Subsequently, morphological reconstruction and boundary tracing algorithms are utilized to obtain edges of the binary mask. A more specific road extraction algorithm proposed in focuses on the high resolution satellite images, and roads are considered as the regions having continuity and homogeneity properties [16]. Therefore, the authors aim to detect road surfaces rather than road lines. For this purpose, the input image is roughly segmented with a technique called as homogram segmentation exploiting both of the spatial and spectral characteristics of the data. Before homogram construction step, the input image is exposed to contrast stretching and Gaussian smoothing operations to attain histograms having proper shapes for homogram segmentation. Then, several morphological operations are applied on the result of homogram segmentation to obtain a more accurate road mask. The method suggested in the study employs mathematical morphology together with active contour model (snakes) to detect roads from high resolution satellite images [35].

The authors combined the input taken from human operator with well-known Bayesian filters such as Kalman and particle filters [36]. An initial road profile is identified by human operator. Then, the next state of the tracker is estimated by Bayesian filter. The state model consists of current coordinates of the tracker, direction of the road and change in road direction. The observation model is obtained by matching the reference model with the observed profile. The proposed approach is superior to many automatic road extraction algorithms existing in the literature.

An automatic road extraction algorithm which operates on 15 meters LANDSAT Enhanced Thematic Mapper (ETM) panchromatic images is proposed in [22]. This study firstly defines the basic characteristics of roads according to their geometric, radiometric, topologic and contextual features. Dual road edge following method is applied to the edge map of the image. False positives are eliminated by validating the roads' spectral homogeneity and structural properties. The authors indicate that this method needs to be extended by using different information or techniques to show good performance on different types of images.

An automatic road extraction algorithm using aerial images is proposed in [15]. They consider roads as long and thin structures depicting high contrast with respect to their neighbourhoods. Based on roads directional rectangularity, bounded width and contrast properties, the algorithm firstly extracts candidate road segments called footprints. The footprints are identified by utilizing the spoke wheel operator which is type of a directional angular operator. Then, footprints are classified as road and non-road regions by using a Bayes model in order to eliminate false positives. The features for this model are extracted by a rule based approach called toe-finding algorithm which mainly analyzes the directional variety of road or non-road footprints. In the Bayesian decision model a lognormal model distribution is constructed by using area-to-perimeter ratios of road footprints. In a more recent study, the authors propose a new method considering two main difficulties faced in the road extraction problem; identifying initial seeds and a robust tracking strategy [20]. An adaptive Canny based method detects edges of the input image. This edge information is fed to the Harris corner detection algorithm to determine interest points. Beginning from these points, seeds are selected by the help of context features such as adjacency, parallelism, perpendicularity and intersection of line segments. This automatic seed selection procedure is based on a newly proposed algorithm called as bat algorithm. Seed points induced by context objects other than roads are eliminated by firstly creating a circular search region at the given seed and then validating its presence with pre-defined rules. Then, initial road tracking position and direction are determined, and a r ectangle reference template is also constructed by using initial seeds. A variation of mutual information matching method is used to track roads along the main road axis.

In this paper, road network extraction from high resolution satellite images has been developed based on Otsu Thresholding and Genetic Algorithm segmentations. The image is first enhanced using high pass filter. Image sharpening can be achieved in the frequency domain by a high-pass filtering process. High-pass filter will attenuate the low-frequency components without disturbing high frequency information. Then the resulted image is segmented using Otsu Thresholding and Genetic Algorithm.

Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either falls in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum [37].

In a Genetic Algorithm, a population of strings called chromosomes which encode candidate solutions to an optimization problem evolves toward better solutions [32]. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (crossover and mutation) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

A segmentation operation followed by morphological operation renders structural evaluation of the road parts within the multi-resolution analysis framework [23]. The extracted features are fed into performance analysis based on the metrics RI, GCE and VOI.

2 Algorithm Comparison

2.1 Data Preprocessing

2.1.1Enhancement in frequency domain

An objective of enhancement is to process a given image so that the result is more suitable than the original image for a specific application.
Two broad methods are possible:

1. Spatial domain techniques and
2. Frequency domain techniques

Here concentrate only on Frequency domain techniques. The convolution theorem is based on frequency domain techniques. Consist of the following spatial domain operation:

$$g(x,y) = h(x,y) * f(x,y) \tag{1}$$

The convolution theorem state that following frequency domain connection holds:

$$G(u,v) = H(u,v) \cdot F(u,v) \tag{2}$$

Where G, H and F are the Fourier transforms variables of g, h and f respectively. H is known as the transfer function of the process. Many image enhancement problems can be articulated in the form of the above equation. The purpose is to select a transfer function that changes the image in such a way that some feature of the image is enhanced.

2.1.2 General concept:

The frequency filters process an image in the frequency domain. Application of this type of filtering is easy:

1. Transform the image into the Fourier domain
2. Multiply the image by the filter
3. Take the inverse transform of the image

All frequency filters can also be implemented in the spatial domain and, if there exists a simple kernel for the desired filter effect, it is computationally less expensive to perform the filtering in the spatial domain. Frequency filtering is more appropriate if no straight forward kernel can be found in the spatial domain, and may also be more efficient.

The operator usually takes an image and a filter function in the Fourier domain. This image is then multiplied with the filter function in a pixel-by-pixel fashion:

$$G(u,v) = F(u,v) * H(u,v) \tag{3}$$

Where F(u,v) is the input image in the Fourier domain, H(u,v) the filter function and G(u,v) is the filtered image.

To obtain the resulting image in the spatial domain, G (u,v) has to be retransformed using the inverse Fourier transform. There are basically three different kinds of filters: low-pass, high-pass and band-pass filters.

2.1.3 High-pass filtering

Image sharpening can be achieved in the frequency domain by a high-pass filtering process. High-pass filter will attenuate the low-frequency components without disturbing high frequency information.

Consider zero-phase-shift filters that are radially symmetric and can be completely specified by cross section extending as a function of distance from the origin at center.

$$D(u,v)=\sqrt{u^2+v^2} \tag{4}$$

Filter Function:

$$H(u,v)=1-e^{-D^2(u,v)/2D_0^2} \tag{5}$$

The basic model is as shown:

$$f(x,y) \to \boxed{\ln} \to \boxed{FFT} \to \boxed{H(u,v)} \to \boxed{IFFT} \to \boxed{e} \to g(x,y)$$

As the color and brightness values for each pixel are interpolated some image softening is applied to even out any fuzziness that has occurred. To preserve the impression of depth, clarity and fine details, the image processor must sharpen edges and contours. It therefore must detect edges correctly and reproduce them smoothly and without over-sharpening. The result of this method is shown in Fig. 3b

2.2 Otsu thresholding based segmentation

To set a global threshold or to adapt a local threshold to an area, usually looking at the histogram to see if one can find two or more distinct modes one for the foreground and one for the background. Recall that a histogram is a probability distribution:

$$p(g)=\frac{n_p}{n} \tag{6}$$

That is, the number of pixels having grayscale intensity g as a fraction of the total number of pixels n.

Converting a grayscale image to monochrome is a common image processing task. Otsu's method, named after its inventor Nobuyuki Otsu, is one of many binarization algorithms. This section describes how the algorithm works and provides a Matlab implementation, which can be easily ported to other languages.

Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either falls in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum.

Define the within-class variance as the weighted sum of the variances of each cluster:

$$\sigma^2_{within}(n)=n_B(T)\sigma^2_B(T)\pm n_0(T)\sigma^2_0(T) \tag{7}$$

Where

$$n\,p(T)=\sum_{i=0}^{T-1} p(i) \tag{8}$$

$$n_0(T)=\sum_{i=0}^{T-1} p(i) \tag{9}$$

$\sigma^2_B(T)$=The variance of the pixels in the background (below
threshold)

$\sigma^2_0(T)$=The variance of the pixels in the foreground (above threshold)

Where [0, N− 1] is the range of intensity levels.

Computing this within-class variance for each of the two classes for each possible threshold involves a lot of computation, but there's an easier way. If you subtract the within-class variance from the total variance of the combined distribution, you get something called the between-class variance:

$$\sigma^2_{between}(T)=\sigma^2-\sigma^2_{within}(T)$$

$$=n_B(T)[\mu_B(T)-\mu]^2+n_0(T)[\mu_0(T)-\mu]^2 \tag{10}$$

Where combined variance and μ is the combined mean. Notice that the between-class variance is simply the weighted variance of the cluster means themselves around the overall mean. Substituting $\mu=n_B(T)+\mu_B(T)+n_0(T)+\mu_0(T)$ and simplifying, to get

$$\sigma^2_{between}(T)=n_B(T)n_0(T)[\mu_B-\mu_0]^2 \tag{11}$$

So, for each potential threshold T:

1. Separate the pixels into two clusters according to the threshold.
2. Find the mean of each cluster.
3. Square the difference between the means.
4. Multiply by the number of pixels in one cluster times the number in the other.

This depends only on the difference between the means of the two clusters, thus avoiding having to calculate differences between individual intensities and the cluster means. The optimal threshold is the one that maximizes the Between-class variance (or, conversely, minimizes the within-class variance). This still sounds like a lot of work, since have to do this for each possible threshold, but it turns out that the computations aren't independent as change from one threshold to another. Can update $n_B(T)$, n_0 (T), and the respective cluster means $\mu_B(T)$ andμ_0 (T) as pixels move from one cluster to the other as T increases. Using simple recurrence relations can update the between-class variance as successively test each threshold:

$$n_B(T+1) = n_B(T) + n \quad (12)$$

$$n_0(T+1) = n_0(T) + n \quad (13)$$

$$\mu_B(T+1) = \frac{\mu_B(T) n_B(T) + n_T T}{n_T(T+1)} \quad (14)$$

This method is sometimes called the Otsu method. It's easy to implement Otsu algorithm here the steps of algorithm.

1. Compute histogram and probabilities of each intensity level.
2. Set up initial n_B (0) and $\mu_B(0)$
3. Take all possible thresholds T=1…..maximum intensity
4. Update n_B and μ_B
5. Compute $\sigma_B^2(T)$.
6. Desired threshold corresponds to the maximum $\sigma_B^2(T)$.

The result of this algorithm is shown in Fig. 3c

2.3 Genetic Algorithm Based Segmentation

In a Genetic Algorithm, a population of strings called chromosomes which encode candidate solutions to an optimization problem evolves toward better solutions. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (crossover and mutation) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached

2.3.1 Genetic algorithm procedure

Genetic Algorithm consists of the following steps:

Step 1: Choose the initial population of individuals

Step 2: Evaluate the fitness of each individual in that population

Step 3: Repeat on this generation until termination (time limit,sufficient fitness achieved etc.):

i. Select the best-fit individuals for reproduction.
ii. Breed new individuals through crossover and mutation operations to give birth to offspring
iii. Evaluate the individual fitness of new individuals
iv. Replace least-fit population with new individuals

The inherent power of a genetic algorithm lies in its ability to exploit, in a highly coefficient manner, information about a large number of individuals. By allocating more reproductive occurrences to above average individuals, the overall net effect is an upward shift in the population's average fitness. Since the overall average moves upward over time, the genetic algorithm is a "global force" which shifts attention to productive regions (groups of highly fit individuals) in the search space. However, since the population is distributed throughout the search space, genetic algorithms effectively minimize the problem of converging to local maxima.

2.3.2 Binarization

In any image analysis or enhancement problem, it is essential to identify the objects of interest from the rest. Binarization is required to separate the foreground portion from background in the images.

In the present work, Otsu's method [Otsu, 1979] is used to perform histogram shape based image thresholding. The algorithm assumes that the image to be binarized contains two classes of pixels (e.g. foreground and background); it then calculates the optimum threshold separating those two classes so that their combined spread (within-class variance) is minimal. In Otsu's method it exhaustively search for the threshold that minimizes the within-class variance, defined as a weighted sum of variances of the two classes. The segmented image after binarization in which the road (foreground) pixels are separated from the background are shown in Fig. 3d and 4a.

2.3.3 Removal of Small Regions

After binarization, the image can be viewed as road and non road features where the road is an elongated region contain maximum area and other non road features such as trees buildings, houses have minimum area. Image which containing minimum region area is set to false and maximum region area is set to true to retain the road features. The result is shown in Fig. 3e and 4c.

2.3.4 Morphological Operations

The mathematical morphology tools are exploited after edge detection and thresholding to improve the edge detection output. After finding the best filters, threshold, the image analysis process has been performed over the entire image of the study area.

Since by making any pixel less than T as 0 to detect roads, there are chances of detecting dark vehicles, shadows, and trees, which have intensity values less than T (i.e. range similar to that of roads). It can be observed that roads are dark in color. It can also be observed that there are some isolated black pixels, which correspond to dark vehicles, shadows, and trees. To minimize the detection of shadows, dark vehicles, and trees, apply four morphological operations: Clean, Thin, Bridge, and Holes to the binary image.

As a result of these four morphological operations, most of the isolated dark pixels will be eliminated. In the particular case where large areas are covered by trees and vegetation (with intensity values in the range of roads), the possibilities of being eliminated are minimal. This is due to the fact that these large areas are not isolated set of pixels and the morphological operations, which are restricted to a 3 -by-3 block of pixels, will not eliminate them. If try to increase the size of the block, there are possibilities of missing the roads. Fig. 3f and 3g, Fig. 4d and 4e, Show the binary image obtained after applying the morphological operations.

3 Performance Analysis

The algorithms have been implemented using MATLAB. The performance of image segmentation approaches are analyzed and discussed. The measurement of image segmentation is difficult to measure. There is no common algorithm for the image segmentation. The statistical measurements could be used to measure the quality of the image segmentation. The rand index (RI), global consistency error (GCE) and variations of information (VOI) are used to evaluate the performance. The detailed description with formulae of RI, GCE and VOI parameters are explained in detail as follows.

3.1 Performance Metrics

3.1.1 Rand Index

The Rand index (RI) counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth averaging across multiple ground truth segmentations. The Rand index or Rand measure is a measure of the similarity between two data clusters. Given a set of n e lements and two partitions of S to compare, and, define the following:

a - The number of pairs of elements in S that are in the same set in X and in the same set in Y
b - The number of pairs of elements in S that are in different sets in X and in different sets in Y
c - The number of pairs of elements in S that are in the same set in X and in different sets in Y
d - The number of pairs of elements in S that are in different sets in X and in the same set in Y

The Rand index (R) is,

$$R = \frac{a+b}{a+b+c+d} = \frac{a+b}{\binom{n}{2}} \tag{15}$$

Where, a + b as the number of agreements between X and Y and c + d as the number of disagreements between X and Y. The Rand index has a value between 0 and 1, with 0 indicating that the two data clusters do not agree on any pair of points and 1indicating that the data clusters are exactly the same[38].

3.1.2 Variation of Information

The Variation of Information (VOI) metric defines the distance between two segmentations as the average conditional entropy of one segmentation given the other, and thus measures the amount of randomness in one segmentation which cannot be explained by the other [21]. Suppose two clustering (a division of a set into several subsets) X and Y where X = {X1, X2... Xk}, pi = | Xi | / n, n = Σ k | Xi |. Then the variation of information between two clustering is:

$$VI(X; Y) = H(X) + H(Y) - 2I(X, Y) \tag{16}$$

Where, H(X) is entropy of X and I(X, Y) is mutual information between X and Y. The mutual information of two clustering is the loss of uncertainty of one clustering if the other is given[38].

Thus, mutual information is positive and bounded by {H(X), H(Y)} _log2 (n)

3.1.3 Global Consistency Error

The Global Consistency Error (GCE) measures the extent to which one segmentation can be viewed as a refinement of the other. Segmentations which are related are considered to be consistent, since they could represent the same image segmented at different scales. Segmentation is simply a division of the pixels of an image into sets. The segments are sets of pixels. If one segment is a proper subset of the other, then the pixel lies in an area of refinement, and the error should be zero. If there is no subset relationship, then the two regions overlap in an inconsistent manner.

The formula for GCE is as follows,

$$GCE = \frac{1}{n}\min\{\sum_i E(s1, s2, pi), \sum_i (s2, s1, pi)\} \quad (17)$$

Where, segmentation error measure takes two segmentations s1and s2 as input, and produces a real valued output in the range [0::1] where zero signifies no error. For a given pixel pi consider the segments in s1 and s2 that contain that pixel[38].

4 Experimental Results

The experiment is conducted in the image using the algorithms Otsu thresholding and Genetic algorithm and their results shown in Fig.2 with required statistical parameters and their results are presented in Table 1. If the value of RI is higher and GCE, VOI are lower, then the segmentation approach is better.

Method	Rand Index	Global Consistency Error	Variation of Information
OTSU Thresholding	0.8828	0.1078	0.5547
Genetic Algorithm	0.8999	0.0935	0.5081

Table 1-Comparative Analysis of Performance of the Segmentation Techniques

4.1 Performance Evaluation

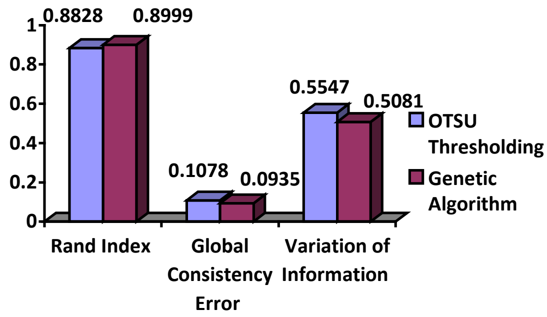


Fig. 2 Performance analysis of GA and OTSU methods

The Performance analysis chart shown in Fig. 2 reveals that the rand index of improved Genetic algorithm is higher than Otsu thresholding and also the global consistency error and variation of information are lower than it. Comparatively the GA algorithm provides good result. So it was observed that the proposed method GA performs better compare to Otsu thresholding approach.

Fig. a

Fig. b

Fig. c

Fig. d

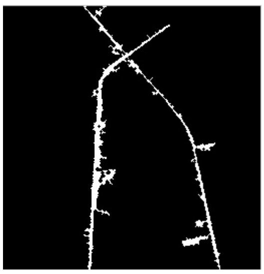


Fig. e

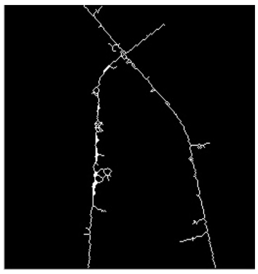


Fig. f

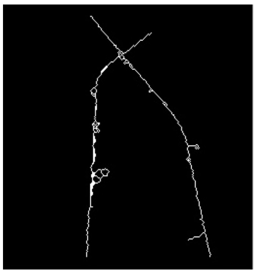


Fig. g

Fig. 3 a . Original Image b. E nhanced Image c. Result of Otsu Thresholding Segmentation d. Binarized Image of Otsu thresholding result. e. Result after removal of small regions f,g. Result after applying morphological operations.

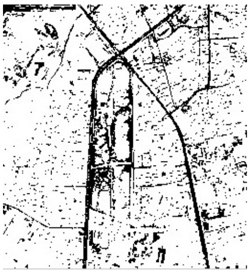


Fig. a

Fi g. b

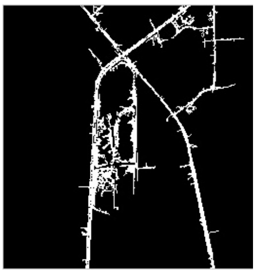
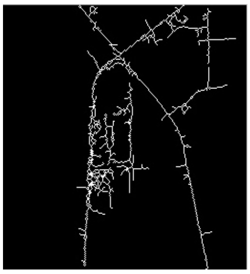


Fig. c



F ig. d

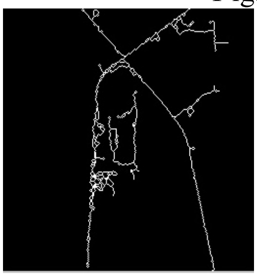


Fig. e

Fig. 4 a. Result of Genetic Algorithm based segmentation b. Binarized Image of GA r esult c. Result after removal of small regions d,e. Result after applying morphological operations

Fig. 5 Ground Truth Image

5 Conclusion

By using the two algorithms better results are obtained for GA based segmentation. OTSU method assumes that the histogram of the image is bimodal (i.e., two classes). The method breaks down when the two classes are very unequal (i.e., the classes have very different sizes). The correct maximum is not necessary the global one. The selected threshold should correspond to a valley of the histogram. - The method does not work well with variable illumination. The region under work should include only road segments, and trees, buildings and houses should be avoided. The presence of bushes and trees decrease the accuracy of the results since those objects. The algorithms would cluster trees that are very close to each other, causing an error in the final detection of roads.

In GA based segmentation, it provides better quality segmentation results in a minimal number of segmentation cycles. It is expected that the genetic algorithm will visit only a small percentage of the search space to achieve the global maximum.

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