CHAPTER 4

RURAL ROAD CLASSIFICATION SYSTEM

Though a lot of work has been done in the road network extraction the rural road network extraction remains a challenging problem. A handful literary work can be found in this field. Mena et al. (2005) work shows that they worked on SAR images for the extraction of roads from the semi-urban and rural roads. It is difficult to extract rural road network due to lack of efficient and reliable automatic extraction algorithms to deal with certain poorly addressed, difficult issues that generally occur in high resolution aerial and satellite images for example, blurring, broken or missing road boundaries, lack of road profiles, heavy shadows, and interfering surrounding objects.

To extract roads from the rural areas, the proposed classification system has four stages of processing, namely, image segmentation, morphological operation, dominant objects extraction
and neural network-based classification. In the segmentation process, the images are segmented using a pre-developed region-scalable fitting model. Then, the dominant objects are extracted after performing a two-stage morphological operation. Finally a well-trained neural network has been used to extract roads from the given satellite image.

In this chapter, while Section 4.1 introduces the active contour models, Section 4.2 discusses region based active contour models. Section 4.3 describes the region scalable fitting energy; morphological operations are discussed in Section 4.4. Dominant object extraction and ANN based road identification are detailed in Sections 4.5 and 4.6 respectively. Results and discussion are presented in Section 4.7 and conclusion is provided in Section 4.8.

**4.1 ACTIVE CONTOUR MODELS**

Automatic road network extraction from the satellite imagery has been a major research direction in the photogrammetric and computer vision fields for more than two decades. Different types of satellite images and variation in the resolutions of input images can cause difficulties in the extraction of the road networks that do not conform to a specific global shape. There are three generic steps to road extraction: road finding, road tracking, and road linking. Different combinations of these three steps constitute various algorithms for road extraction.

In semi-automatic approaches, the operator provides information such as starting points and directions. Starting points are used as seed points and starting directions assist road tracking (Vosselman et al. 1995). Algorithms then predict the trajectory of the road in incremental steps until reaching a stopping criterion.

With the automatic detection of road seed points, semi-automatic approaches may be upgraded to automatic ones. Barzohar et al. (1996) presented an automatic approach for the selection of
starting points based on a gray values histogram. In Baumgartner et al. (1999), roads are modeled
as a network of intersections and links between these intersections, and are found by grouping
processes. Amini et al. (2002) used an object-based approach for automatic extraction of major
roads. This approach consists of two parallel stages. In the first stage, an image containing the
road is segmented and straight line segments are extracted. In the second stage, the resolution of
the image is reduced and converted to a binary image. The road skeleton in the binary image is
then extracted. By combining the results from these two stages, the road sides are extracted.

In the last few years the deformable models have been used as a powerful tool for object and
surface modeling as well as two-dimensional and three-dimensional image segmentation in
applications as diverse as medical imaging, graphics, robotics, and terrain-modeling.

In the research on road extraction, considerable work has been done for the segmentation of two-
dimensional and three dimensional shapes with a few seed points. Agouris et al. (2001) extended
the snake models or active contour models to change detection of road segments. However,
methods based on the traditional snake model have the following drawbacks:

- **Initialization:** The initial curve must be placed close to the object boundary and is tedious to
draw. The initial curve and the desired object boundary differ greatly in size and shape. The
model must be re-parameterized dynamically to recover the object boundary. This process
requires some additional computation.

- **Minimization:** A local minimum of energy, such as spurious edges caused by noise, may stop
the evolution of the snake unexpectedly.

- **Topology:** This method is difficult when dealing with topological changes. If multiple objects
appear in the image and an initial curve surrounds them, all the objects cannot be detected.
Additional splitting and merging approaches are needed to solve this problem. These increase the complexity of the snake implementation significantly.

There are several advantages of active contour models (snakes) over classical image segmentation methods, such as edge detection, thresholding and region grow. Active contour models

- Can achieve sub-pixel accuracy of object boundaries,
- Can be easily formulated under a principled energy minimization framework, allow incorporation of prior knowledge, such as shape and intensity distribution, for robust image segmentation.
- They can provide smooth and closed contours as segmentation results, which are necessary and can be readily used for further applications, such as shape analysis and recognition.

Existing active contour models can be categorized into two major classes: *edge-based models* and *region-based models*. Edge-based models use local edge information to attract the active contour towards the object boundaries. Region-based models aim to identify each region of interest by using a certain region descriptor to guide the motion of the active contour. However, popular region-based active contour models tend to rely on intensity homogeneity in each of the regions to be segmented.

Intensity inhomogeneity often occurs in real images from different modalities. In the satellite images, the brightness due to the reflectance from the earth’s surface and due to the signal interactions with atmospheric particles can be seen as image noise. Also, pixels found in the shadows have a different value of intensity/gray level/colour from the ones that are in the open area, representing the same use of land. This reduces the accuracy of classification.
Seasonal variations, insect attacks, droughts and/or the inclination of land become the main factor which limits the identification of the land use. Impact of illumination and reflectance and such effects caused by variations of angles and illumination intensity, time of the day when image is captured also cause the intensity inhomogeneities.

Intensity inhomogeneity was addressed by the models presented by Vese et al. (2002) for general images. To minimize the Mumford–Shah functional (1989), both models cast image segmentation as a problem of finding an optimal approximation of the original image by a piecewise smooth function but these models are computationally extensive. Michailovich et al. (2007) work with active contour model using the Bhattacharyya difference between the intensity distributions inside and outside a contour. Their model does not rely on the intensity homogeneity and, therefore, to some extent, overcome the limitation of PC models.

Chumming Li et al. (2008) presented a region-based active contour model in a variational level set formulation. A data fitting energy is defined as a region-scalable fitting (RSF) energy functional in terms of a contour and two fitting functions that locally approximate the image intensities on the two sides of the contour. The region-scalability of the RSF energy is due to the kernel function with a scale parameter, which allows the use of intensity information in regions at a controllable scale, from small neighborhoods to the entire domain. This energy is then incorporated into a variational level set formulation with a level set regularization term. In the resulting curve evolution that minimizes the associated energy functional, intensity information in local regions at a certain scale is used to compute the two fitting functions and, thus, guide the motion of the contour toward the object boundaries. Due to the level set regularization term in the proposed level set formulation, the regularity of the level set function
is intrinsically preserved to ensure accurate computation for the level set evolution and final results, and avoid expensive re-initialization procedures.

4.2 REGION-BASED ACTIVE CONTOUR MODELS

Mumford et al. (1989) formulated the image segmentation problem as for given an image \( I \), and a contour \( C \) has to be found which segments the image into non overlapping regions. Let \( \Omega \subset R^2 \) be the image domain, and \( I: \Omega \subset R \) be a given gray level image. The Mumford-Shah energy equation is given as:

\[
F_{MS}(u, C) = \int_{\Omega} (u - I)^2 \, dx + \int_{\Omega \backslash C} |\nabla u|^2 \, dx + \nu |C| \tag{4.1}
\]

where \( |C| \) is the length of the contour \( C \). The minimization of Mumford–Shah functional results in an optimal contour \( C \) that segments the given image \( I \), and an image \( u \) that approximates the original image \( I \) and is smooth within each of the connected components in the image domain \( \Omega \) separated by the contour \( C \).

Vese et al. (2001) proposed an active contour approach to the Mumford–Shah problem for a special case where the image in the equation (4.1) is a piecewise constant function. For an image on the image domain, Chan-Vese proposed to minimize the following energy:

\[
F_{CV}(C, c_1, c_2) = \lambda_1 \int_{\text{outside } C} |I(x) - c_1|^2 \, dx + \lambda_2 \int_{\text{inside } C} |I(x) - c_2|^2 \, dx + \nu |C| \tag{4.2}
\]

where \( \lambda_1, \lambda_2 \) and \( \nu \) are positive constants, outside \( C \) and inside \( C \) represent the regions outside and inside the contour \( C \), respectively, and \( c_1 \) and \( c_2 \) are two constants that approximate the image intensity in outside \( C \) and inside \( C \). The optimal constants \( c_1 \) and \( c_2 \) minimize the first
two terms which are also called global fitting energy. $c_1$ and $c_2$ are the average of the intensities in the entire regions inside $C$ and outside $C$ respectively. By using an energy functional (introduced by Vese et al. (2001)) on a level set function $\Phi$ and two smooth functions $u^+$ and $u^-$ that are defined on the regions outside and inside the zero level contour of a level set function $\Phi$, respectively. The energy functional has a data fitting term, which describes the approximation of the image by $u^+$ and $u^-$ in their corresponding sub-regions, and a smoothing term that forces $u^+$ and $u^-$ to be smooth.

4.3 REGION SCALABLE FITTING ENERGY MODEL

The region-scalable fitting model is used in the proposed classification system for the purpose of segmentation [Li et al., (2008)]. Let $I(a,b); a=0,1,\ldots,M-1, b=0,1,\ldots,N-1,$ be the satellite image in RGB color space with $I_R, I_G$ and $I_B$ be the RGB components respectively. In most of the satellite images the water is displayed as blue, bare soil as red and vegetation as green. This combination leads to a pseudo natural colour composite. Since the proposed method is for the extraction of the rural road network, which are usually bare soil/mud roads with no specific boundaries, hence red component of the image has been considered for the segmentation.

As per the segmentation model, an energy has been derived, is given as

$$
E = \sum_{i=1}^{2} \lambda_i \left( \int K_\sigma (X-Y) | I_R(Y) - f_i(X) |^2 M_i(\varphi(Y)) dX + \nu \int \nabla H_\varepsilon(\varphi(X)) dX \right)
$$

(4.3)

where,

$$
K_\sigma (X) = \frac{e^{-|X|^2 / 2\sigma^2}}{(2\pi)^n / 2\sigma^n}
$$

(4.4)
\[ M_1(\varphi) = H_e(\varphi) \]  \hspace{1cm} (4.5)

\[ M_2(\varphi) = 1 - H_e(\varphi) \]  \hspace{1cm} (4.6)

In Equation (4.3), \( \lambda_1, \lambda_2 \) and \( \mu \) are positive constants, \( K_\sigma \) is the Gaussian kernel, which is given as Equation (4.4), \( H_e(\varphi) \) is the Heaviside function, \( I_R(Y) \) is the intensity contribution because of localization property, \( f_1(x) \) and \( f_2(x) \) are fitting values and \( E \) is the local intensity fitting energy. The consolidated energy function to be minimized is given as

\[ F = E + \mu \left[ \frac{1}{2} \left( |\nabla \varphi(X)| - 1 \right)^2 \right] dX \]  \hspace{1cm} (4.7)

Based on the fitting energy, a level set evolution equation, which has to be solved in the segmentation model, is defined as

\[
\frac{\partial \varphi}{\partial t} = -\delta_e(\varphi)(\lambda_1 e_1 - \lambda_2 e_2) + \nu \delta_e(\varphi) \text{div} \left( \frac{\nabla \varphi}{|\nabla \varphi|} \right) + \mu \left( \nabla^2 \varphi - \text{div} \left( \frac{\nabla \varphi}{|\nabla \varphi|} \right) \right) \]  \hspace{1cm} (4.8)

where,

\[ e_i(X) = \int K_{\sigma}(Y - X) \left| I(X) - f_i(Y) \right|^2 dY \hspace{0.5cm} ; i = 1,2 \]  \hspace{1cm} (4.9)

with the aid of the curve equation and due to the kernel function in data fitting term, the intensity information present in the local regions are extracted to guide the movement of the contour and so a segmented image \( S_R(a, b) \) is obtained from the region-based scalable fitting energy model. The obtained \( S_R \) is in grayscale and it is converted to binary image \( S_B \) and subjected to morphological operation viz., dilation and closing.
4.4 MORPHOLOGICAL OPERATION

The segmented image \( S(x, y) \) which is a binary image is subjected to dilation and the resultant is morphologically closed. The morphological operations are explained below.

**Dilation:** The structuring element \( S_{E1} \) is a line with the properties of width \( \omega \) and degree \( \theta \). This structuring element can be defined as a vector of size \( |S_{E1}| \). The dilated image \( D \) is defined as \( D = S_R \oplus S_{E1} \). However, this can be mathematically illustrated as follows

\[
w_i(z) = S\left(\frac{i}{M - |S_{E1}| + 1}, z + \left(i\% (M - |S_{E1}| + 1)\right)S_{E1}(z)\right)
\]  
(4.10)

where, \( w_i(z) \) is the window of elements taken from the image \( S \); \( i=0,1,\ldots, N_w - 1 \) and \( z = 0,1,\ldots, |S_{E1}| - 1 \), \( N_w \) is the number of windows determined from the image, which can be determined as \( N_w = M(N-|S_{E1}|+1) \). Based on the window elements, dilated window of pixels \( d_i(z) \) are determined as follows

\[
d_i(z) = \begin{cases} 
1; & \text{if } w_i(0.5|S_{E1}|) = 1 \\
0; & \text{otherwise}
\end{cases}
\]  
(4.11)

from \( d_i(z) \), \( D \) is obtained by initially generating an empty matrix with image size and then placing the \( d_i(z) \) window elements in \( D \) at the corresponding positions from which the elements are taken.

**Morphological closing:** The dilated image \( D \) is subjected to the morphologically close operation with a structuring element disk is selected with the properties of size \( d_{size} \). The dilation operation is mathematically illustrated above and the erosion is mathematically modeled below, even the erosion can be defined as
\[ C = D' \ominus S_{E2} \quad (4.12) \]

where, \( S_{E2} \) is the structuring element for morphological closing and \( D' \) is the dilated image of \( D \). Similarly as done in Equation (4.10), the window of elements is extracted from \( D' \) using \( S_{E2} \). From the window of elements, the eroded pixels are determined as follows

\[
c_i(0.5|S_{E2}|) = \begin{cases} 
1; & \text{if } w_i = I \\
0; & \text{otherwise}
\end{cases} \quad (4.13)
\]

where, \( I \) is the Identity matrix, here it is of size \( 1 \times |S_{E2}| \) and \( c_i \) is eroded pixels of \( i^{th} \) window. The final morphologically closed image \( C \) is obtained by initially generating an empty matrix and then by placing \( c_i \) at the corresponding positions in \( C \).

### 4.5 Dominant Objects Extraction

In this processing stage, the objects that dominate in the image are extracted in an effective way. To perform this, the resultant of the morphing stage, \( C \) is complemented using Equation (4.14) and so \( C' \) is obtained.

\[
C'(a,b) = \begin{cases} 
1; & \text{if } C(a,b) = 0 \\
0; & \text{if } C(a,b) = 1
\end{cases} \quad (4.14)
\]

In \( C' \), the total number of objects is identified by determining the number of connected components. \( C' \) is the complement image of connected white pixels or a group of white pixels that represent an object. Let, \( n_{obj} \) be the total number of objects present in \( C' \). From each object, say \( O_k \), \( k = 0,1,\cdots,n_{obj}-1 \), one of the most popular object properties called as area is measured. Generally, area is a two-dimensional quantity which represents the amount or extent of surface or an object. Here, the area of \( O_k \) is determined by counting the number of pixels in
the object (or number of white pixels enclosed by the object) i.e., the number of pixels of an object defines its area. Based on the determined area, a set of dominant objects \( \{O^d\} \) is determined as

\[
\{O^d\} = \{O^d\} \cup \{O_k\}; \quad if \ |O_k| > A_T
\]  

(4.15)

where, \( A_T \) is a threshold for area. If the criterion is not satisfied, the object is not considered as the dominant objects. A mask \( C_D \) with image size is generated and the pixels of the dominant objects are placed in the position as it is in \( C' \).

4.6 ANN BASED ROAD IDENTIFICATION

For accurate classification of the land use from the satellite imagery, traditionally statistical minimum distance (MD) classifiers have been used. But these classifiers depend on assumptions that may limit their utilities for many datasets. In the last decade extensive work has been carried out by employing Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for the road classification. In both the tools, the objects to be classified belong to either one or the other class. The work done by Xiong et al. (2010) shows that ANN perform slightly better than the SVM in urban Land Usage/Coverage (LUC) extraction from ETM+ images because of their high accuracy and good performance. Buddhiraju et al. (2010) emphasized on the analysis and usage of different advanced image classification techniques like Cloud Basis Functions (CBFs) Neural Networks, ANN and SVM for object based classification to get better accuracy. The work concluded by stating that the ANN classifier trained using the standard back-propagation algorithm produced marginally better results compared to the other methods, (though the CBF is a relatively new technique in the remote sensing arena requires further study).
Also, SVM learning often results in a large number of SVs, which should be stored and computed in classification. ANN classifiers have much less parameters, and the number of parameters is easy to control. Hence, ANNs require less storage and computations than SVMs.

The image $C'$, which has the dominant objects, is used to identify the roads. To perform this, multilayer feed forward neural network is used. The structure of ANN used in the system is depicted in Figure 4.1. The network is constructed by three input nodes, one hidden node and an output node. The basis function for the input layer is given in Equation (4.16) and the activation functions for hidden and output layer are given in Equation (4.17) and Equation (4.18) respectively.

$$g = \alpha + \sum_{q=1}^{3} W_q x_q$$  \hspace{1cm} (4.16)

$$y' = \frac{1 - e^{-g}}{1 - e^{-2g}}$$ \hspace{1cm} (4.17)

$$y = y'$$  \hspace{1cm} (4.18)

**Figure 4.1** Multi layer, feed forward neural network
In Equation (4.16), \( \begin{bmatrix} x \end{bmatrix} \) is the input matrix of size \( N_R \times 3 \) with image pixels. To make the ANN to perform its task, it is necessary to train the ANN. Once trained, the ANN can classify the road pixels from the other objects in a given input satellite image. The ANN training phase and classification phase is given below.

**Training Phase:** The constructed feed forward network is trained using Back Propagation (BP) algorithm. To train the network effectively, sufficient data samples are needed. To generate them, numerous satellite images of rural area are collected. Manually, the road pixels are determined from them and the input training vector is generated as

\[
\begin{bmatrix}
    r^{(r)}_1 \\
    r^{(r)}_2 \\
    r^{(r)}_3 \\
\end{bmatrix} = \begin{bmatrix}
    I^{\text{train}(r)}_R \\
    I^{\text{train}(r)}_G \\
    I^{\text{train}(r)}_B \\
\end{bmatrix}, \quad l = 0,1,\cdots, N^{(r)}_{SR} - 1 \text{ and } r = 0,1,\cdots, N_I - 1, \quad \text{where, } I^{\text{train}(r)}_R, I^{\text{train}(r)}_G \text{ and } I^{\text{train}(r)}_B \text{ are the } R, G \text{ and } B \text{ components of } r^{th} \text{ sample image, respectively, } N^{(r)}_{SR} \text{ is the number of road pixels present in } r^{th} \text{ sample image and } N_I \text{ is the number of sample images. The input vectors, which are determined from every sample image } I_{r}, \text{ are used to train the network. The step-by-step procedure of training process is given below.}

1. Generate arbitrary weights within the interval \([0,1]\) and assign it to links between the input layer and hidden layer as well as to the links between the hidden layer and output layer.

2. Input training pixel vector to the network and determine the output of input layer, hidden layer and output layer using Equation (4.16), Equation (4.17) and Equation (4.18), respectively.

3. Determine BP error using
\[
\gamma = \frac{1}{N_I} \sum_{i=0}^{N_I-1} \left( \frac{1}{N_{SR}^{(r)}} \sum_{j=0}^{N_{SR}^{(r)-1}} |G - y_{lr}| \right)
\]  

(4.19)

where, \( \gamma \) is the BP error, \( G \) is the target output.

4. Adjust the weights of all the neurons based on the determined BP error and obtain new weights using

\[
W^{new} = W^{old} + \Delta W
\]  

(4.20)

In Equation (4.20), \( \Delta W \) is the weight to be changed and that can be determined as \( \Delta W = \eta \cdot y_{lr} \cdot \gamma \), where, \( \eta \) is the rate of network learning and \( y_{lr} \) is the network output obtained for \( l^{th} \) pixel in \( r^{th} \) image.

5. Repeat the process from step 2 until the BP error gets minimized to a minimum extent.

In practical case, the termination criterion is \( \gamma < 0.1 \).

**Classification Phase:** In the classification phase, the roads present in \( I \) is marked with the aid of the trained network, but on the basis of \( C_D \). From \( C_D \), the coordinates of all white pixels are determined and a coordinate vector \( V^{co} \) is formed. The determined \( V^{co} \) is of size \( N_U \times 2 \), which represents the \( a-b \) coordinates of the image, where, \( N_U \) is the number of white pixels present in \( C_D \). The RGB components of \( I \), which are indicated by \( V^{co} \), termed as

\[
x_p = [I_R(V^{co}_{p1}, V^{co}_{p2}) \ I_G(V^{co}_{p1}, V^{co}_{p2}) \ I_B(V^{co}_{p1}, V^{co}_{p2})]
\]

are determined. The obtained \( x_p \) is of size \( N_U \times 3 \) and each row of the vector is given as input to the well-trained network. The network
provides an output for every row vector of \( x_p \), which can be given as \( y_p \). A decision making process is performed over \( y_p \) using Equation (4.21) and so the roads of \( I \) are marked.

\[
I_R(V_{p1}^{co}, V_{p2}^{co}) = \begin{cases} 
0 & ; y_p \leq G \\
I_R(V_{p1}^{co}, V_{p2}^{co}); otherwise 
\end{cases} 
\] (4.21.a)

\[
I_G(V_{p1}^{co}, V_{p2}^{co}) = \begin{cases} 
255 & ; y_p \leq G \\
I_G(V_{p1}^{co}, V_{p2}^{co}); otherwise 
\end{cases} 
\] (4.21.b)

\[
I_B(V_{p1}^{co}, V_{p2}^{co}) = \begin{cases} 
0 & ; y_p \leq G \\
I_B(V_{p1}^{co}, V_{p2}^{co}); otherwise 
\end{cases} 
\] (4.21.c)

Using the above equations, the roads are identified and marked in the given input satellite image \( I \). Hence, in the given input satellite image \( I \) for rural area, the roads are effectively marked using the proposed classification system.

### 4.7 RESULTS AND DISCUSSION

This section is divided into three parts; the first part (subsection 4.7.1) is the implementation and result of the algorithm and comparison with other methods from the literature. The second section (subsection 4.7.2) shows the results of the algorithm when implemented on different satellite images selected with varied objects of interest. The third section (subsection 4.7.3) gives the results and comparison when noise images are used as input to the algorithm and checks the robustness of the algorithm.
4.7.1 IMPLEMENTATION ON RURAL SATELLITE IMAGES AND COMPARISON

The proposed classification system is implemented in the working platform of MATLAB (version 7.10). Training the network using different sample satellite images of rural areas with extracted roads is necessary, prior to testing the system. After completing the training process, test images are given as input to the proposed classification system to evaluate its performance. The resultant imageries (Figures 4.2, 4.3, 4.4, 4.5, 4.6) obtained from the intermediate steps as well from different stages of processing of the proposed system is given below.

**Figure 4.2 (a)** Rural satellite image input to the effective rural road classification system (www.satelliteimaging.com), (b) Segmented rural satellite image

(a) ![Image](image1.png) (b) ![Image](image2.png)

(a) ![Image](image3.png) (b) ![Image](image4.png)

(c) ![Image](image5.png) (d) ![Image](image6.png)
Figure 4.3 Segmentation results (a) formation of the initial contour in the image (b) contour convergence after 20\textsuperscript{th} iteration (c) contour convergence after 100\textsuperscript{th} iterations, (d) contour convergence after 200\textsuperscript{th} iterations and (e) segmented image

Figure 4.4 Morphological operation performed on the segmented rural satellite image: (a) dilation $w=3$ and $\theta=0$, (b) closing , $d_{size}=1$

Figure 4.5 Dominant object extraction with $A_T = 40$ (a) input or complementary image and (b) dominant object extracted image

Figure 4.6 Road network extraction (a) marked image (ANN input) and (b) road extracted image (ANN output)
Figure 4.2 shows the original satellite image that is given as input to the proposed system and the image containing only the R component that is given as input to the segmentation process. The image with initial contour, contour convergence after 20th, 100th and 200th iterations and the segmented image are shown in Figure 4.3.

Figure 4.4 shows images obtained from the two morphological operations, dilation and morphological closing. The dilation is performed using line element with properties $\sigma = 3$ and $\theta = 0^\circ$. The morphological closing operation is performed with disk element with parameters $d_{size} = 1$. The dominant objects are extracted with $A_T = 40$ (to qualify as a road, the object needs to have a minimum number of road pixels, 40 pixels were used to describe the properties of the road class in a representative way satisfactorily) and the obtained imageries are shown in Figure 4.5. The final decision making process of the classification phase is performed using the target threshold of 0.3. The ANN classification phase results are affixed in Figure 4.6.

The performance of the proposed system is evaluated using standard quality measures such as completeness, correctness and quality. The resultant evaluation measures are given in Table 4.1 and it was observed that the proposed system has competently extracted the roads from satellite imageries of rural areas and attained a significant level of performance in the evaluation results. The proposed algorithm was also applied to a rural road network with straight roads made of concrete. The extracted road network is shown in Figure 4.7. The extracted standard quality measures are shown in Table 4.2.

Baillioeu (2005) used active contours and prior knowledge for change analysis, Wang et al. (2003) used classification, tracking, and morphology, Yu et al. (2004) used a rough segmentation based on straight line density, Idbraim et al. (2008) used adaptive directional
filtering, segmentation, grouping and evaluation. The result obtained by the above algorithm was compared with four different methods show that the proposed methods performance was not sufficient (Table 4.3 and Figure 4.8).

**Table 4.1** Performance of the effective rural road classification system using ANN in terms of standard quality measures

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>Performance Metrics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Length of road extracted</td>
<td>6381</td>
</tr>
<tr>
<td>2</td>
<td>Length of road extracted (matched)</td>
<td>5121</td>
</tr>
<tr>
<td>3</td>
<td>Length of reference extracted</td>
<td>7442</td>
</tr>
<tr>
<td>4</td>
<td>Length of road extracted (unmatched)</td>
<td>3581</td>
</tr>
<tr>
<td>5</td>
<td>Completeness (in %)</td>
<td>68.81</td>
</tr>
<tr>
<td>6</td>
<td>Correctness (in %)</td>
<td>80.25</td>
</tr>
<tr>
<td>7</td>
<td>Quality (in %)</td>
<td>46.45</td>
</tr>
</tbody>
</table>

**Figure 4.7:** Application of effective rural road classification system to a rural image with straight roads (www.satelliteimaging.com)

**Table 4.2** The standard quality measures of the rural image with straight roads

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>Performance Metrics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Completeness (in %)</td>
<td>70.83</td>
</tr>
<tr>
<td>2</td>
<td>Correctness (in %)</td>
<td>65.66</td>
</tr>
<tr>
<td>3</td>
<td>Quality (in %)</td>
<td>41.15</td>
</tr>
</tbody>
</table>
Table 4.3 Comparison of standard quality measures of the effective rural road classification system using ANN with different methods

<table>
<thead>
<tr>
<th>Measure</th>
<th>Bailloeul</th>
<th>Wang</th>
<th>Yu</th>
<th>Idbraim</th>
<th>Rajani Mangala</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completeness</td>
<td>0.5003</td>
<td>0.6542</td>
<td>0.8240</td>
<td>0.82</td>
<td>0.6881</td>
</tr>
<tr>
<td>Correctness</td>
<td>0.7112</td>
<td>0.3784</td>
<td>0.4625</td>
<td>0.67</td>
<td>0.7296</td>
</tr>
<tr>
<td>Quality</td>
<td>0.4158</td>
<td>0.3153</td>
<td>0.4374</td>
<td>0.58</td>
<td>0.4380</td>
</tr>
</tbody>
</table>

Figure 4.8: Comparison of the effective rural road classification system with other methods

4.7.2 IMPLEMENTATION OF ALGORITHM ON SEMI-URBAN SATELLITE IMAGES

When the algorithm was tried on different type satellite images, viz., plain straight roads with intersections, curved roads, fly-over, short roads inside a residential colony etc., the algorithm’s performance i.e., the extracted standard quality parameters to the reference parameters show about 60% completeness, but the correctness and quality parameters are not satisfactory (refer to Figure 4.9, Figure 4.10 and Table 4.4). The calculation is based on the length of the road extracted and matched and not on the efficiency of the algorithm in extraction of the road network.
Table 4.4 The standard performance parameters of different types of satellite images

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Image1</th>
<th>Image2</th>
<th>Image3</th>
<th>Image4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completeness</td>
<td>0.4330</td>
<td>0.4901</td>
<td>0.6150</td>
<td>0.6561</td>
</tr>
<tr>
<td>Correctness</td>
<td>0.3478</td>
<td>0.3243</td>
<td>0.3169</td>
<td>0.3302</td>
</tr>
<tr>
<td>Quality</td>
<td>0.1804</td>
<td>0.1659</td>
<td>0.1621</td>
<td>0.1666</td>
</tr>
</tbody>
</table>

Figure 4.9 Application of the effective rural road classification system to different types of satellite images.
(a) satellite image 1 (b) satellite image 2 (c) satellite image 3 (d) satellite image 4

The algorithm did not work effectively on different types of images and it fails to extract the curves, the joints between the intersections and different levels of roads i.e., the flyover etc. As mentioned earlier the efficiency of the road networks extracted depends on the comparison of the road network length (manually extracted from the original image) to the length of the road network manually extracted after the proposed algorithm is run. In the images 2 and 3, a lot of other features were also extracted, which led to an increase in the length of the extracted road network, hence decrease in the efficiency.
4.7.3 ROBUSTNESS OF THE EFFECTIVE RURAL ROAD CLASSIFICATION ALGORITHM

Yan Li (2009) show that the completeness, correctness and quality parameters of results of their experiments on the high resolution aerial and satellite images with heavy noise are 85% and 97% respectively. The results of this algorithm however when checked for robustness by adding 5% salt and pepper noise gave the about 80% completeness and 28% correctness and quality of 14.6% (Table 4.5 and Figure 4.11). However, the algorithm gave less than 60% completeness and about 15% correctness when checked for 2% speckle noise.

Table 4.5 The performance parameters of the effective rural road classification system to different types of satellite images with 5% noise added to the images.

<table>
<thead>
<tr>
<th></th>
<th>Image 1</th>
<th>Image 2</th>
<th>Image 3</th>
<th>Image 4</th>
<th>Image 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completeness</td>
<td>0.7411</td>
<td>0.8101</td>
<td>0.8099</td>
<td>0.8260</td>
<td>0.8206</td>
</tr>
<tr>
<td>Correctness</td>
<td>0.2712</td>
<td>0.2879</td>
<td>0.2873</td>
<td>0.2801</td>
<td>0.2871</td>
</tr>
<tr>
<td>Quality</td>
<td>0.1427</td>
<td>0.1508</td>
<td>0.1479</td>
<td>0.1433</td>
<td>0.1459</td>
</tr>
</tbody>
</table>

Figure 4.10: The performance parameters of the effective rural road classification system applied to different satellite images
4.8. CONCLUSION

In this chapter, an effective road classification system that extracts roads from the satellite images of rural areas and semi-urban areas has been implemented and a collection of satellite imagery has been used to train the network. Test images were given to the system and the results have been evaluated. The extraction performance has been validated by standard quality measures such as completeness, correctness and quality.

For the rural areas from the quality measures, it can be visualized that the proposed system has performed well in extracting the roads of rural areas. As the roads of rural areas have no proper layout, considerable complexity is involved in the extraction process. Under this circumstance, the designed system has proved its efficacy by reaching a satisfactory level of performance in extracting roads from rural area satellite imagery.
The complexity in the extraction of the semi-urban roads include the intersections, the flyovers, more than one level of the road, the curvature of the road, the short roads inside the residential colonies and inside the factories, more than one parallel road (which counts the roads and the separators into different roads), the lanes, by-lanes and the service roads etc., The designed system considers all the areas greater than 40 as roads, hence all the unwanted features like the lanes, by-lanes, roads inside residential colonies, jogging tracks etc., are identified as roads. This led to a decrease in the standard quality parameter values which are measured with respect to the manually extracted roads from the images. Hence, the road network extraction from the semi-urban areas was not satisfactory.

The algorithm was tried for different rural and semi-urban noisy images to check the robustness, and the algorithm performed well considering the actual results are only about 60%.