Railway Vegetation Detection System

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Abstract

The objective of this thesis work is to propose an algorithm to distinguish between Vegetation and Man-made objects on the railway track and then measure the amount of Vegetation between each pair of sleepers, with high speed and high detection rate. The Vegetation is detected in two phases. Firstly, the vegetation is detected in RGB color space by considering the green (G) priority. Secondly, the remaining vegetation is extracting from the image in HSV color space by considering the 'Hue' value with different values of 'Value'. The sleepers' position are detected by texture segmentation by entropy filtering and also assumed where necessary with respect to the rail line position with an accuracy of 93.75%. The position of the rail line was detected by Hough Transform and Interpolation with an accuracy of 96.75%. The system was tested on 87 images of natural light condition and the execution time of each image was calculated in between 5.765 sec to 6.534 sec for image size 400x600 pixels on an ordinary laptop computer with a 1.60 GHz AMD E-350 Processor, RAM 4 GB (3.60 useable), Windows 7 Home Premium, MATHLAB Version 7.10.0.499(R2010a). The system correctly detects vegetation in 90.87 % of the vegetated image regions. Only 0.43 % of the manmade object pixels are falsely detected as vegetation. For detecting vegetation, the vegetation detection part was also applied on different images like forest or garden and it shows excellent performance and robustness.

Acknowledgment

First I would like to thank to The Almighty Creator for making me and for his uncountable blessing.

Foremost, I would like to thank my supervisor Dr. Siril Yella for his continuous kind support and guidance for my thesis work. Without his constant encouragement and motivation the thesis work would not have been completed. For his patience, motivation, enthusiasm and immense knowledge my thesis became very smooth.

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Chapter 1

INTRODUCTION

1.1 Importance of vegetation detection

Railway is one of the three most important transportation systems. Our modern life, directly or indirectly, depends on this system. Vegetation on the railway tracks such as weeds or grass is a threat for the safety and service standards in the rail service. For example: Fallen leaves of the plants form lubrication on the rails. The braking distance of the train is increased. Dry vegetation is flammable. Fire damages the infrastructure. Trains are scratched by the weeds which causes damage. Contact of the trees with the overhead communication system causes short circuits. Vegetation on the track such as weeds or grass reduces the elasticity of the ballast. Roots of the trees along the rail have the same affect on the ballast by storing water in it, which causes frost breaks in winter. So, vegetation management programme is very important for ensuring high safety and service standards along the railway lines. It is also important for maintenance crews for their operation safely.

1.2 Problem Definition

In our image there are two types of vegetations: 1) Green vegetation (alive) and 2) Brown Vegetation (almost dead or dead vegetation).Green vegetation can be easily detected by color segmentation because in the image there is only one type of green object which is the green vegetation. But in the case of brown vegetation, it is little bit difficult to detect because some parts of the wooden sleepers and iron rail are also brown.

Furthermore, for measuring the amount of vegetation between each pair of sleepers we need to know the position of each sleeper. The sleeper does not have a uniform color and we do not get fix shape or size of them in many pictures because they are partially or totally covered by the vegetation. So we need to take the help of the rail line positions to detect the position of the sleepers. Since sleepers are always perpendicular to the rail line. And, in the case of rail line detection, some part of the rail is rusty and in some cases their edges are covered by the vegetation .For this reason we are not getting sharp edges of the rail in those pictures. This makes it difficult to detect the rail lines by using Hough transform only.

1.3 Proposed Approach

In this thesis work, a vegetation detection and measurement algorithm that can detect and measure vegetation with high speed has been described. This method gives good performance even if the pictures are taken in a bad lighting condition. At first color segmentation technique has been used to segment the green priority color region (green vegetation) and non-green priority color region in RGB color space. Rest of the vegetation (especially Brown vegetation) is segmented by color segmentation technique in HSV color space. Then they are added up to estimate the total vegetation. But, the problem is during brown vegetation detection in HSV color model, some parts of the rail, wood, sleeper and stone are also incorrectly detected as vegetation which they are not. Almost all the cases they are comparatively very small in size. If we use a size filter after detecting the total vegetation and remove the comparatively very small objects form the vegetation image then we can overcome this problem. So, we get the total vegetation without noise. After the vegetation detection, we need to measure the amount of vegetation between each pair of sleepers. For that, first we detect the rail lines by Texture segmentation, Hough Transform and interpolation function. Then, detect the position of the sleeper by texture segmentation. After that I shall draw a perpendicular line from the centroids of each sleeper to each rail line. Finally we calculate the total amount of vegetation between each pair of sleepers.

1.4 System architecture

For detecting the vegetation, first we compute the Green priority in RGB color space by a formula, ExG=2*G-R-B where R is Red, G is Green and B is Blue. This technique is also known as excess green which was previously used in many different reaches [11][12]. Woebbecke et al. (1995a) examined several color indices for weed image segmentation and found excess green and modified hue yielded the best near-binary images of weeds. Meyer et al.(1998) applied ExG to separate plants and soil regions for weed species identification research as well where R, G, B are the un-normalized red, green and blue intensities of the pixel [11]. The threshold for segmentation was determined by the examination of the ExG histogram 'valleys' and also adjusted by the visual observation of the segmented results .For extracting the vegetation from the gray level image of ExG, the threshold has been chosen as 27 for all images.

But this technique has some problem like, it cannot detect vegetation:
1) if the green color is near to white for high light reflection.
2) if the green color is near to black for very low light condition and
3) it cannot detect deep brown vegetation.

To overcome these problems I used the color segmentation process in HSV color space after using the green priority (ExG) technique . The color segmentation process in HSV color

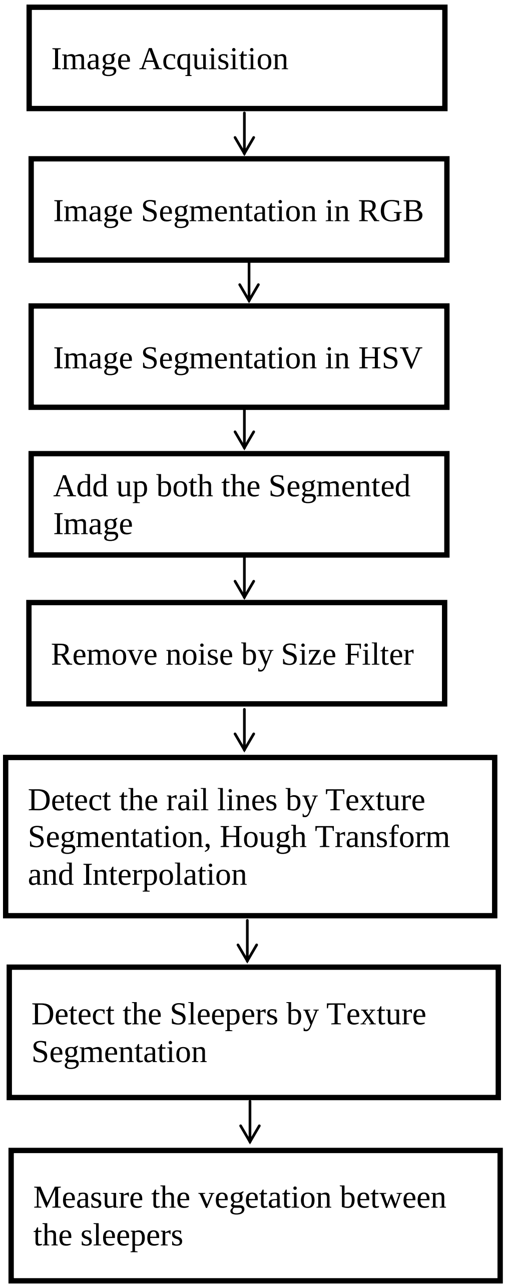

Figure 1.1: Algorithm of vegetation measuring system

space overcome the problems of green priority (ExG) technique of RGB color space. In HSV color space the Green color lays near around 120 degree of hue value. The green vegetation and brown vegetation lies between 150 to 43 degree of hue value. After detecting the vegetation in both the color channel we added up both the vegetation image and got the total vegetation image.

During vegetation detection some parts of the rail, wood, sleeper and stone are also detected as vegetation because their color also brown like brown vegetation. Almost all cases they are comparatively very small in size. To overcome this problem, a size filter is used after detecting the total vegetation and comparatively very small objects are removed from the total vegetation image and obtained results.

In the case of rail line detection, we know that rail lines are straight. So we can detect them by Hough transform. But, a problem is encountered that the Hough transform gives good result only when there are sharp clear edges. In many of our images the rail lines are rusty and their edges are covered by vegetation .As a result, we are not getting good straight edges of rail lines for those images. To detect the rail in the image, we use entropy filter which is a texture filter, Hough transform and interpolation function.

We detect the sleepers by using texture filter (entropy filter). Then we detect the centroids of the sleeper by region properties function in binary image which was followed by the entropy texture image-. After that we draw a perpendicular line from the centroids to each sleeper. Finally, we calculate the total amount of vegetation between each pair of sleepers.

1.5 Previous Research

1.5.1 Measuring Vegetation along Railroads

This thesis work attempts to measure the vegetation on the railway track .Measuring vegetation on the railway track is a totally new work. However, previously, in Austria a study was conducted by Bernhard Hulin and Stefan Schüßler (2005) on measuring railway vegetation. There, they t presented a system to measure the vegetation along the railway tracks not on the railway tracks. Their system consists of three multi spectral cameras that were mounted on a train, which were sensitive in the visible and near infrared spectrum. The aim was to profile the vegetation along rail roads which will provide vegetation register so that the staff can eliminate the vegetation effectively [1].

Two different problems have been solved in that research work
The distinction of Vegetation and Non-vegetation
The 3D-measurement of the vegetation

The use of multi-spectral cameras is necessary for the distinction of green vegetation and the green masts of the overhead contact system. In summer, the spectral system detects vegetation correctly 86.5% of the total vegetated pixels. Where only 0.4% of non-vegetated image regions are misclassified. The 3-D measurement was performed by triangulation [1].

For profiling the vegetation, in Hulin and Schüßler (2005) research, a novel video-based system is offered which automatically profile the vegetation along the tracks at cross and longitudinal sections. Till now in this system, for giving priority according to the safety threat of the vegetation, the system only applies sections and neglects other criteria for instance the number of trains passes during the day. The system was installed on a diagnostic train. The cameras are set up at right angles with parallel optical axes to archive horizontal as well as vertical matching. The horizontal as well as the vertical baseline is 29cm. A small focal length of 12mm had been chosen for reducing the effect of curves [1]. The system works with cameras which detect and profile vegetation up to 10 meters from the center of the track. For each track, the system with this setup, it is able to obtain a rating of vegetation at least once a year. In the system the authors used the passive video-based technologies because they believe that their application is cheaper than active methods.

To separate the green vegetation from the green masts the authors used spectral analysis in the visible and near infrared spectrum (VIS-NIR). The spectral analysis is always faster than the textural analysis because, for the spectral analysis the computer decides for each pixel separately if it belongs to vegetation or not. But in the case of textural analysis , it needs knowledge about the neighboring pixels. Spectral analysis is more robust than textural analysis to segment thin structures of only some pixel width for instance contact wire. In the case of textural analysis, made-made objects surrounded by vegetation are often wrongly classified as vegetation. The third reason for chasseing spectral analysis for segmentation is very difficult to distinguish between the ballast and leafy scrubs. By a textural analysis, segmentation of the leaf-on vegetation on the rail tracks is hardly possible.

In the study the authors used two basic algorithms:

Leaf On Vegetation Segmentation
Leaf Off Vegetation Segmentation

1.5.2 Results & Discussions

To evaluate the system, it is applied manually on both summer and winter images over 100 vegetation regions and non-growing regions.

In summer, the spectral system detects vegetation correctly 86.5% of the total vegetated pixels. Where only 0.4% of non-vegetated image regions are misclassified. It is noted that if the vegetation reflects on the flat surface of the rail, it is detected as vegetation.
Because it happens in both the visible and NIR spectrum. By using any rail detection algorithm the system can overcome this problem.

In winter ,for leaf-off vegetation profiling the edge-frequency detection algorithm gave the best result. With relatively light vegetation on more than 91% and a false detection ratio of the masts of 0.005%. None of the algorithms (Leaf On and Leaf Off) can realistically distinguish between the ballast and vegetation. For small image regions, even the human eye and brain cannot do this either [1].

1.5.3 Limitations & Proposed Solutions of Vision Based Work

Measure vegetation along the railway tracks was done in the field of machine vision. It was performing good but still that work has some limits. They are as follows:

In vision based system the performance vary in different weather conditions and different time of the day. This problem can little bet overcome by using high resolution camera which can detect almost every part of the vegetation.

Furthermore the authors use two algorithms to vegetation detection one for leaf off and another for leaf on season's. They both giving good results. We hope that in future there will be one algorithm to measure vegetation.

THE THEORY

2.1 Image Segmentation

Image segmentation [2] is the process of partitioning an original digital image into multiple homogeneous regions. Where the segments are sets of pixels also known as super pixels. The main aim of segmentation is to modify or simplify the representation of the original image to something which will be more meaningful or easier for analysis. Image segmentation is generally used for locating objects and boundaries (which means lines, curves, etc.) in the images. We can say it is the process of leveling every pixel in an image where pixels with the same label share some visual characteristics. After image segmentation we get some segments where each pixel in the same segments is similar with respect to some properties or characteristic like intensity, color or texture.

2.2 RGB color model

The name of the RGB color model came from the first three letters of the three additive primary colors which are red, green and blue. It is an additive color model which produce a broad array of colors by adding together red, green and blue in various ways. The main purpose of this color model is to sense, represent and display the images in the electronic systems. RGB color model is a device dependent color model. Different devices detect and reproduce a RGB color value differently. The reason behind it is, the color elements (like dyes or phosphors) and their response to the individual R, G and B levels vary from manufacture to manufacture. Even it varies in the same device over time.

2.3 HSV Color Model

The images for my thesis work were taken by a digital camera where those images were in RGB format and we know that RGB format is highly sensitive to the chromatic variation of the daylight.

For this reason any variation in the ambient light intensity affects the segmentation process in RGB color model. For the pattern recognition problem the HSV color model is the ideal color model because it decouples the chromatic and achromatic notion of light. Color segmentation is also ideal in HSV model since Hue feature is invariant to highlights and shadows. HSV stands for hue, saturation, and value. HSV is also called as HSB where B stands for brightness. It is a hex-cone model which has three components (Hue, Salutation and Value). HSV color model is similar to the human color perception which is not always in the case of RGB and CMYK.

2.3.1 Hue

Hue describes the type of the color (such as green, blue etc). It is also the term which describes the dimension of the color that we experience when we look at color. In the HSV color model it angle ranges from 0 to 360 degree.

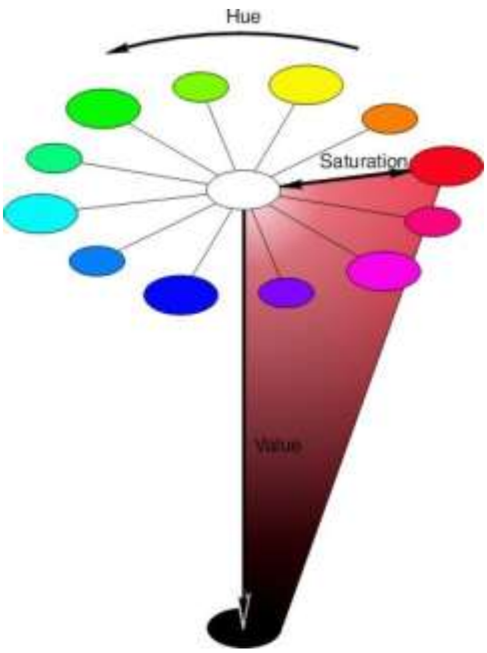

Figure 2.1: A saturation/value slice of a specific hue in the HSV model

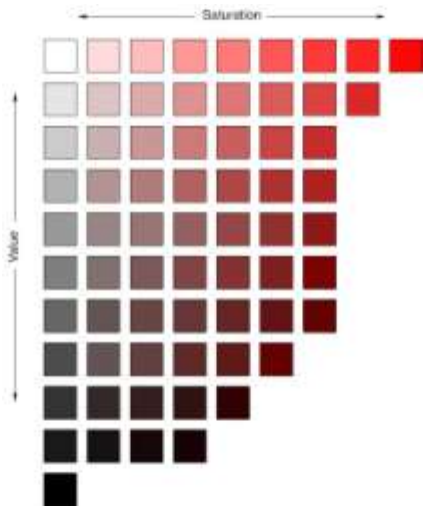

Figure 2.2: Example saturation and value variations on a single red hue

2.3.2 Saturation

Saturation describes the dominance of hue in the color. It is also called the ''purity''. At the outer edge of the hue wheel is pure hue. As near as it comes to the center of the wheel, the purity becomes less and less which means that the color dominates less and less. At the center of the wheel there is no dominance of hue. It is white in the center. So lower the saturation and more grayness comes together. Saturation ranges from 0 to 100 %.

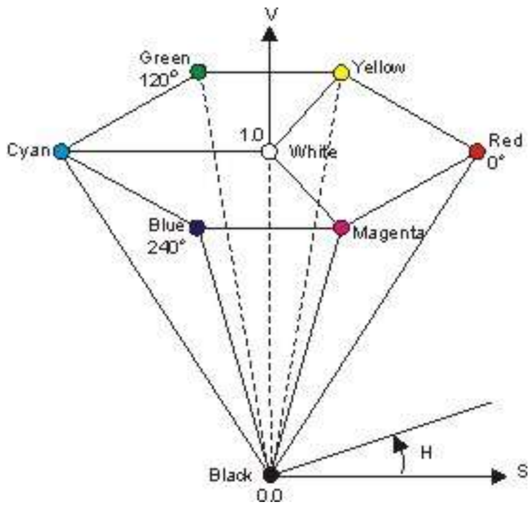

Figure 2.3: HSV color model

2.3.3 Value

Value is the brightness of the color which varies with respect to saturation. It ranges from 0 to 100 %. For 0% the color space will be totally black. According to the spectral definition of the color, it tells about the overall intensity or strength of the light.

2.4 Texture Analysis

In many image processing and machine vision algorithms, image segmentation are made by the uniformity of intensities in local image regions. But in many cases, images of real objects do not show regions of uniform intensities like in the case of railway tracks the intensity and color of the some part of the rail and wood are not uniform. In color and gray image segmentation, the pixel values are assumed that they are spatially independent. But in the case of textured images, they are characterized by the local correlations of pixel values.
In texture analysis, an image is characterized in to regions by their texture content. Texture analysis tries to quantify intuitive qualities expressed by the terms such as rough, smooth, silky, or bumpy as a function of the spatial variation in the pixel intensities. In this sense, the bumpiness or roughness refers to variations in the gray levels or in the intensity values [3].

Texture analysis are used to find texture boundaries, called texture segmentation. Texture analysis are generally used when it is more easier to characterized an object than by the object intensity .It is also used when traditional thresholding techniques do not work effectively.

For detecting sleeper, we face some problems like, the sleepers do not have a fixed color ,shape or size in many images because they are weathered by weather affect and some cases they are partially or totally covered by the vegetation . But only one thing is common among them; it is their texture. So, I tried texture filter like entropy filter and range filter to detect the sleepers. In the experiments, the range filter gave better result when we add up the result of range filter on different color in CMYK color space then entropy filter. But if we used range filter, the time complexity increase a lot .So the entropy filter is used in gray image to detect the sleeper.
In the case of rail line detection, some part of the rail line is rusty and in some cases their edges are covered by the vegetation. For this reason we do not get sharp edges in those pictures. So it becomes difficult to detect the rail lines by using Hough transform only. In this work, we use texture filter (entropy filter), Hough transform and interpolation all together.

2.5 Hough transform

The Hough transform is a popular technique which is used to detect different shapes in binary images. By using Hough Transform it is possible to detect all kind of standard geometric shapes, such as lines, ellipses and circles. But in this work, I am considering only straight lines.

For detecting, the existence of a line, expressed mathematically as

$$y = mx + c$$

the Hough transform algorithm uses an array. The array is known as an accumulator.
The dimension of the accumulator and the number of unknown parameters of the Hough transform problem is equal. For instance, the linear Hough transform problem has two unknown parameters which are the pair (r,θ) or the pair (m,c) . The two dimensions in the accumulator array correspond to quantized values for the (r,θ). For each single pixel and for its neighborhood, the Hough transformation algorithm decides if there is sufficient evidence of an edge at that pixel. If it is, then it will calculate the parameters of that line, after that it looks for the accumulator's bin that the parameters fall into, and increase the value of that bin [4]. By looking for local maxima in the accumulator array which means by finding the bins with the highest values, the all likelihood lines can be extracted, and their (approximate) geometric definitions can be read off. (Shapiro and Stockman) For finding these *peaks*, the simplest way is applying some form of thresholding, but different techniques may give better results in different circumstances - determining which lines are found and how many. The lines which are returned, do not contain any length information. For this reason, it is often very necessary to find out which parts of the image match up with which lines. In addition,

due to imperfection errors in the edge detection step, there will be usually some errors in the accumulator bin, which may leads it non-trivial to find the appropriate peaks, and accordingly the appropriate lines [4].

The result of the Hough transform algorithm is stored in an accumulator matrix. One of the dimension of the matrix are the angles θ values and the other dimension of the matrix stores the distances r, and each element has a value describing how many pixels/points are positioned on a line with parameters (r,θ). As a result the element with the highest value describes what line that is most represented in that image [4].

In this work, we have to measure the amount of vegetation in between each pair of sleeper. But in many images the sleepers are covered partially or fully by the vegetation. In those cases it is difficult to determine the position and alignment of the sleeper. This problem can be overcome if we take the help of the rail position because the sleeper are always perpendicular to the iron rail and they are generally equally spaced in almost all cases. Though the train are always running on the rail, there is no vegetation on the rail line and we know that rail lines are straight. We can detect a straight line object by using Hough transform. Here, with the images we use the Hough transform to detect the rail.

2.6 Morphological Operations

Morphological operations play a very important role in the applications like machine vision and automatic object detection. Morphological operations are generally and mostly performed on the binary image where the pixel values are either 0 or 1. But some can also be performed on the grayscale images. Morphological operation is a broad set of image processing operations which processes the image based on shapes. Morphological operations apply a structuring element on an input image and create an output image of the same size. In the morphological operation, the value of each pixel of the output image comes by a comparison of that corresponding pixel in the input image with its neighbors. Most of the morphological function operates on 3 × 3 pixel neighborhoods. But by choosing the size and shape of the neighborhood, we can construct a morphological operation which is sensitive to specific shapes in the input image [5].

Dilation and erosion are the most basic morphological operations. Dilation adds pixels to the boundaries of the objects in an image and erosion does the opposite. It removes pixels on the object boundaries. How many pixels will be added or removed from the objects in an image is depends on the size and shape of the structuring element which is used to process the image. In the dilation and erosion operations, the state (0 or 1) of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. The rule which is used to process the pixels, defines the operation either it is a dilation or an erosion [5].

In many rail lines images, the lines are rusty and their edges are also covered by vegetation. So if we add pixels to the boundaries of rail lines in the image by Dilation function vertically, we will get better result.

2.7 Interpolation

In numerical analysis, interpolation is a system of producing new data points within the range of a discrete set of known data points. In science and engineering, we regularly has a number of data points which was acquired by experimentation or sampling, that stand for the values of a function for a limited number of values of the independent variable. It is frequently needed to estimate or interpolate the value of the function for an intermediate value of the independent variable. Which may be achieved by regression analysis or curve fitting [6].

Linear interpolation is a technique of curve fitting that uses linear polynomials.

yi = interp1(x,Y,xi,method,'extrap')

For noise in the image, bad light condition, rust on the rail line and uniform straight edge for vegetation we are not a full straight line for the whole rail line. But we know the rail lines are generally straight. So we can assume the full rail line by using interpolation function. In this work we use linear interpolation.

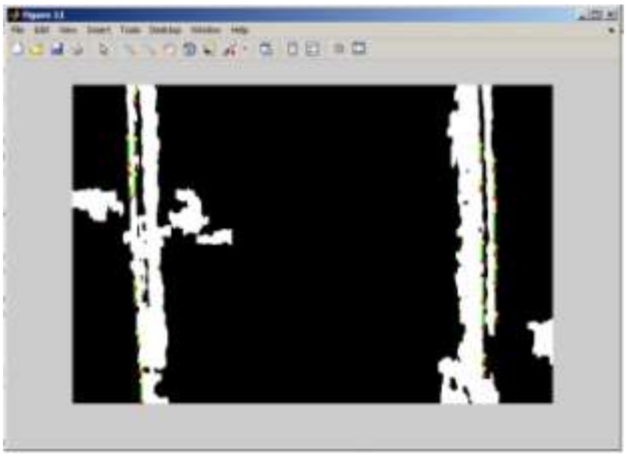

Figure 2.4: Detected rail line by Hough transform

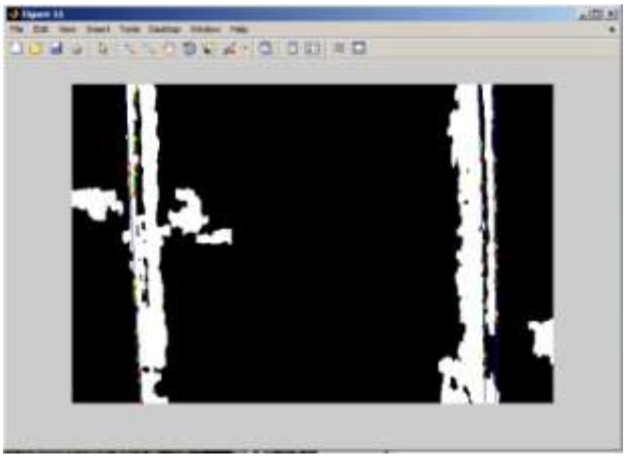

Figure 2.5: Detected full line by Hough transform and interpolation

THE IMPLEMENTATION

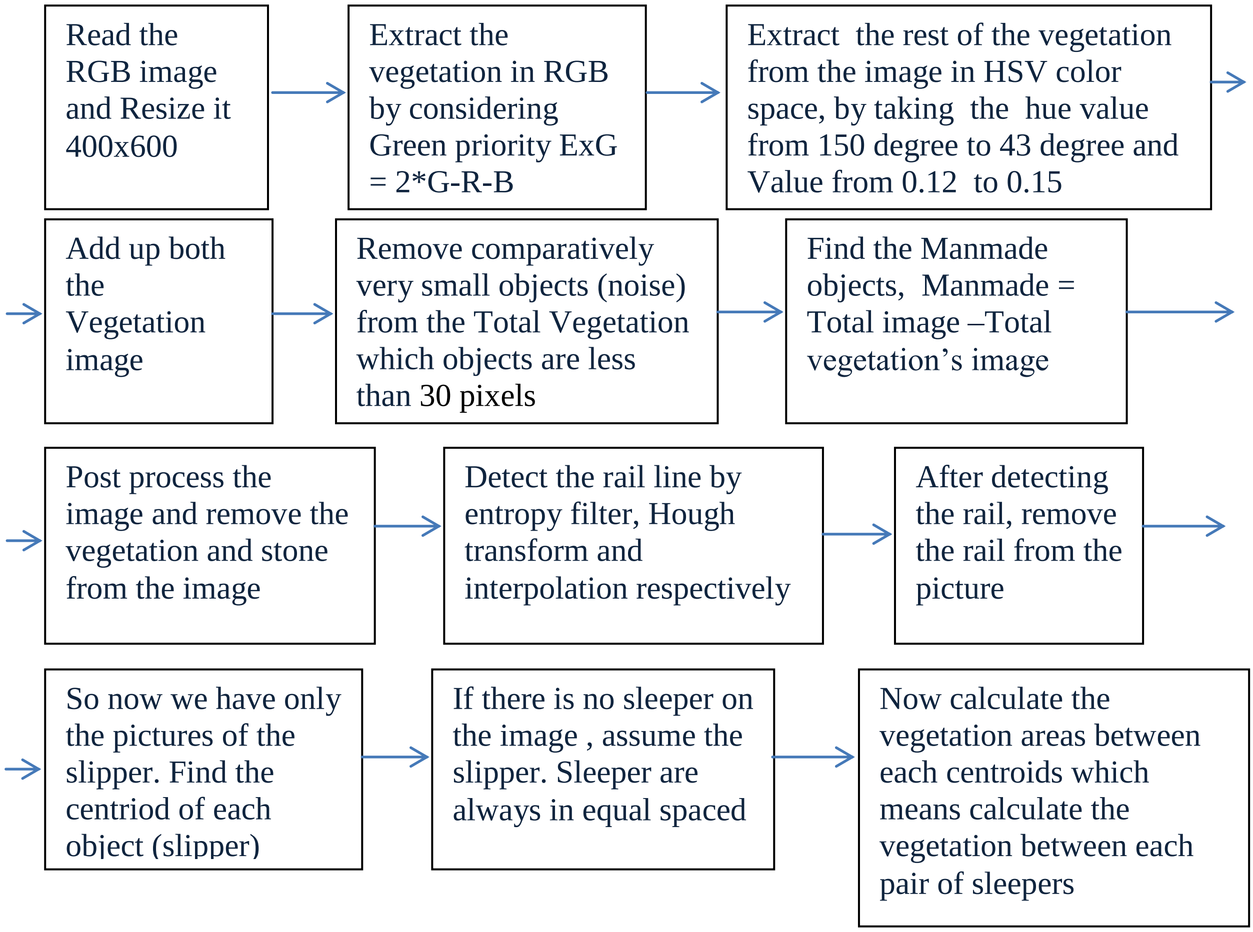

Figure 3.1: Block diagram of image processing of the proposed algorithm

3.1 Extracting the vegetation by Green priority in RGB color space

We detect the total vegetation in two phases. In the first phase we use RGB color space and in the second phase we use HSV color space. In RGB color space, we detect the vegetation by considering the Green color priority. This technique is also known as excess green which was previously used in many different reaches. ‘’Woebbecke et al. (1995a) examined several color indices for weed image segmentation and found excess green (ExG) and modified hue yielded the best near-binary images of weeds. Meyer et al. (1998) applied ExG to separate plant and soil region for weed species identification research as well. [1]’’ where R, G, B are the unnormalized red, green and blue intensities of the pixel. The threshold for segmentation was determined by the examination of the ExG histogram 'valleys' and also adjusted by the visual observation of the segmented results .The threshold is chosen as 27 for all the images used in this work. The threshold has been determined through experimentation.

See Appendix C.1 (Page 49) for a complete discussion concerning the choice of the threshold used in this particular work.

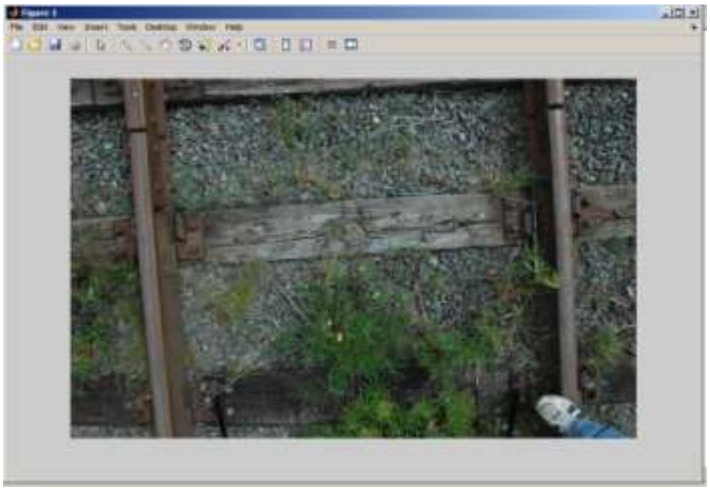

Figure 3.2: Original Image of a rail line.

In RGB color space, all colors are the combination of these three colors ‘Red, Green and Blue’. In the Green Vegetation (and also near to green vegetation) the Green intensity of RGB color space is always greater than Red and Blue colors. So if we apply this formula on an image (G-R)+(G-B)=2*G-R-B (where R, G, B are the unnormalized red, green and blue intensities of the pixel), we will get a Gray Level image where all the objects color near to green will be in white with different intensities depending on the green values and all other objects which is not near to green will be black . A threshold is chosen as 27 for all images to extract the vegetation where the green intensity is higher than red and blue color in RGB color space.

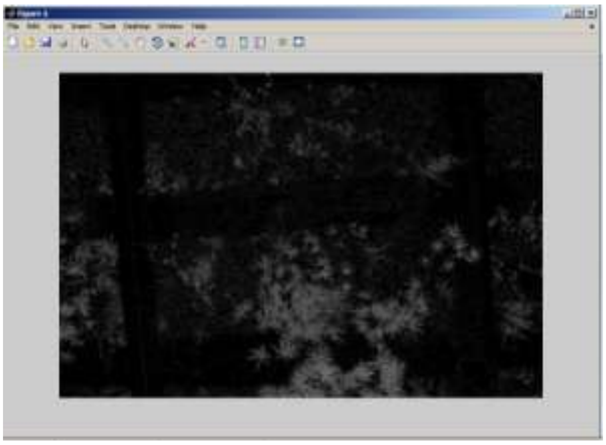

Figure 3.3: Gray level after applying ExG

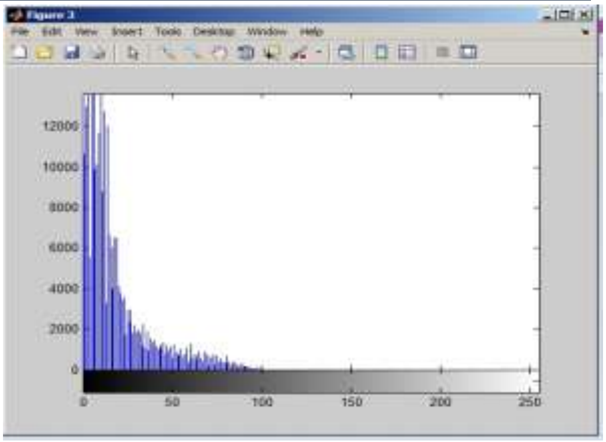

Figure 3.4: Histogram of the ExG Gray level image

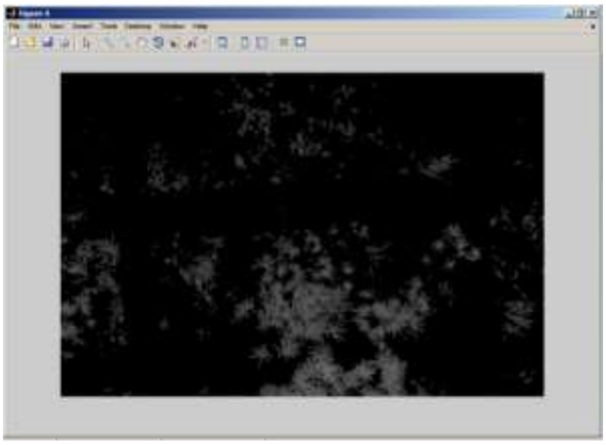

Figure 3.5: Gray level image of detected vegetation after thresholding in ExG image

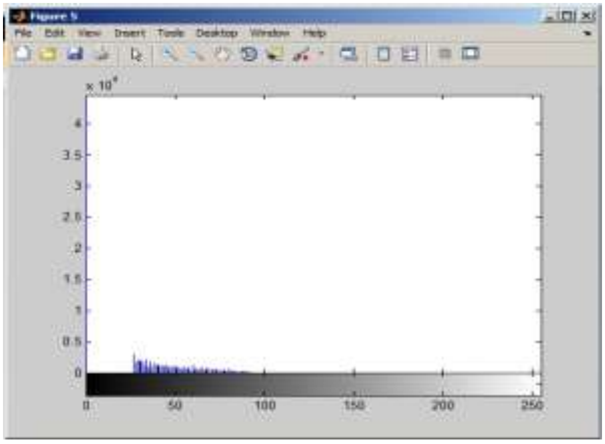

Figure 3.6: Histogram of the detected vegetation image

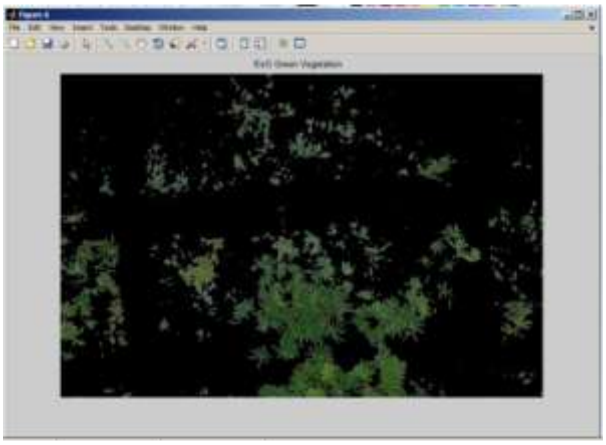

Figure 3.7: Image of Vegetation

Figure 3.8: Image of Manmade objects

3.2 Extracting the rest of the vegetation in HSV color space by thresholding

Green priority technique or Excess Green (ExG) technique has some problems. It cannot detect the green in three cases,
1) if the green color is near to white for high light reflection.
2) the second one is if the green color is near to black for very low light condition.
3) And it cannot detect deep brown vegetation where the green intensity is lower than red and blue intensities.

To overcome these problems we use the HSV color space.

HSV stands for hue, saturation, and value. HSV is also called as HSB where B stands for brightness. It is a hex-cone model which has three components (Hue, Salutation and Value). HSV color model is similar to the human color perception which is not always in the case of RGB and CMYK.

In HSV color model Hue tells about the color. Where Hue angle ranges from 0 to 360 degree. Sometimes Hue calculated in between 0 to 1. Saturation describes the dominance of hue in the color. lower the saturation and more grayness comes together. Saturation ranges from 0 to 100%.

Value is the brightness of the color which varies with respect to saturation. It ranges from 0 to 100%.

For 0% the color space will be totally black. According to the spectral definition of the color, it tells about the overall intensity or strength of the light.

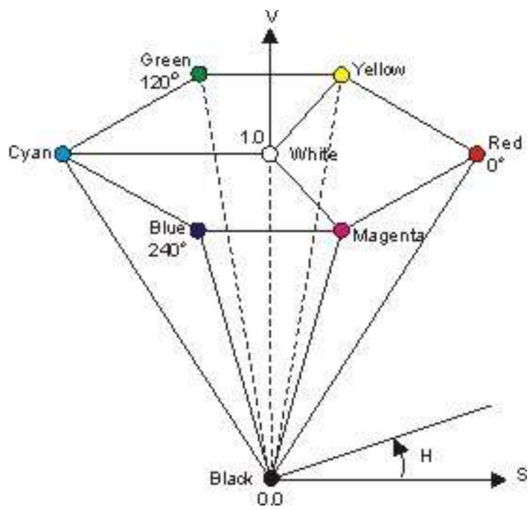

Figure 3.9: HSV color model

In HSV color space the Green color lays near around 120 degree of hue value and the vegetation color (green to brown) lies between 150 to 43 degree of hue value. I extract the rest of the vegetation from the image in HSV color space, by taking the hue value from 150 degree to 43 degree and saturation from 0.12 to 0.15.

The combination of RGB and HSV color segmentation gives better result for vegetation detection. The above combination has been justified in Appendix-C.2 (Page 52).

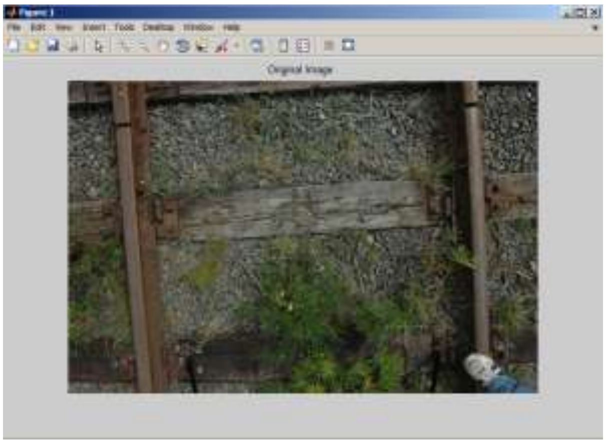

Figure 3.10: Original image

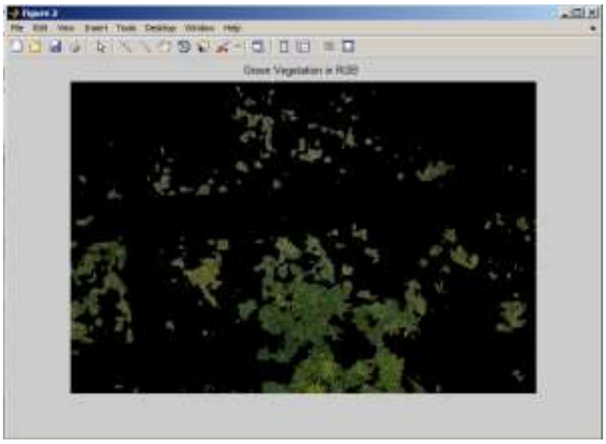

Figure 3.11: Detected vegetation by green priority in RGB

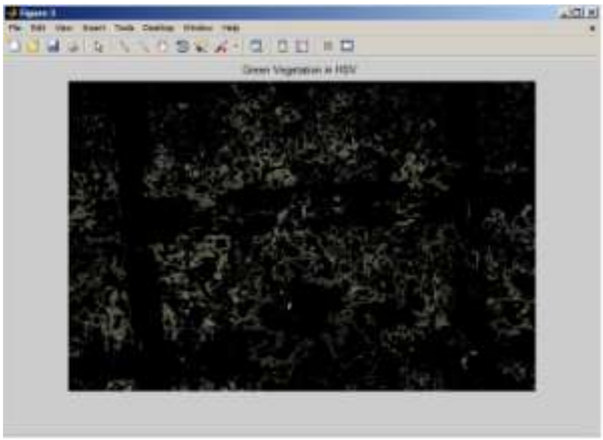

Figure 3.12: Detected vegetation in HSV

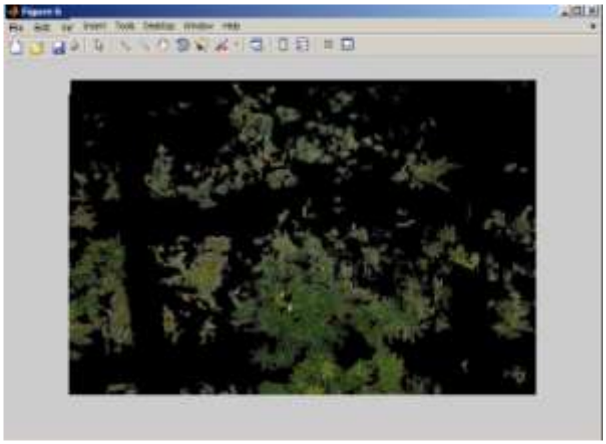

Figure 3.13: Total vegetation detected by both phases in RGB and HSV

3.3 Implementation of Size Filter

Size Filtering is the process of selecting the labeled objects based on the size of the objects. The size of an object is measured by the number of white pixels in that binary image.

During vegetation detection some parts of the rail, wood, sleeper and stone are also detected as vegetation which they are not. Almost all cases they are comparatively very small in size. If we use a size filter after detecting the vegetation and remove the comparatively small objects then we get better result. For removing small objects I use a built in function BWAREAOPEN.

Algorithms of BWAREAOPEN

The basic steps are

1. Find out the connected components
2. Compute the area of each component
3. Remove the small objects depending on a threshold

BW2 = BWAREAOPEN(BW,P) removes all connected components (objects) which have fewer than P pixels from a binary image and produce another binary image BW2.

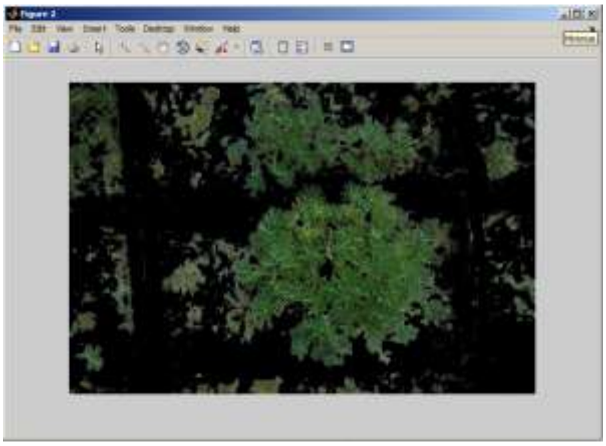

Figure 3.14: Total vegetation with noise.

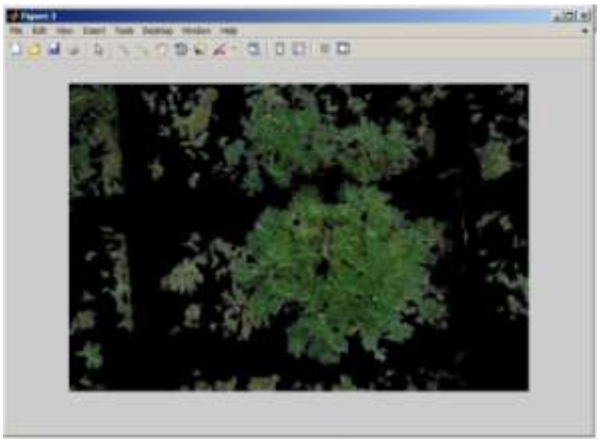

Figure 3.15: Total vegetation after using size filter

3.4 Detecting the rail line:

In our work, we need to measure the amount of vegetation in between each pair of sleepers. But in many cases the sleeper are partially or fully covered by the vegetation. In such a case, it is difficult to determine the position and alignment of the sleeper. We can overcome this problem, if we take the help of the rail line position because the sleeper are always perpendicular to the iron rail and they are generally equally spaced from one another. Though the trains are always running on the rail, so there are no vegetation on the rail line and we know that rail line are straight. We can detect a straight object by using Hough transform. Here in images we use the Hough transform to detect the rail lines. But here is a problem too. The Hough transform give good result when there are sharp clear edges . In many of our images the rail lines are rusty and many cases rail line edges are covered by the vegetation . As a result ,we do not get good straight edges for those pictures. To detect the rail in the image, Texture Segmentation, Morphological Operations dilation, Hough transform and Interpolation function respectively are used.

Figure 3.16: Entropy filtered image for sleeper and line detection.

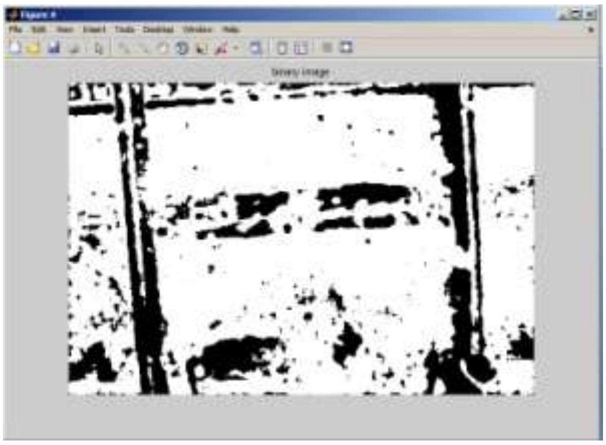

Figure 3.17: Binary image

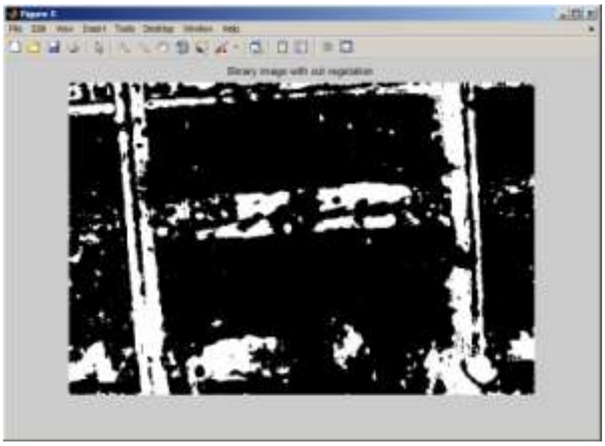

Figure 3.18: Binary image without total vegetation

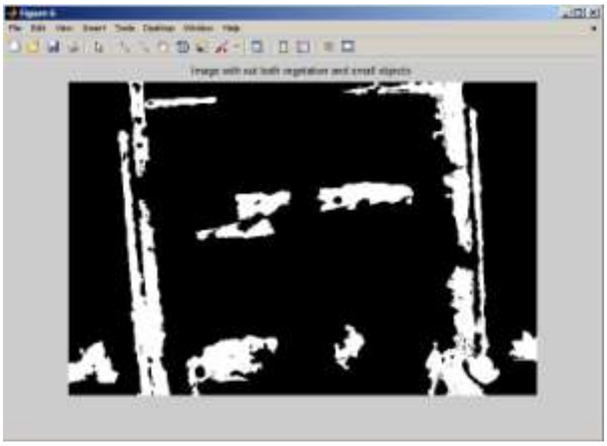

Figure 3.19: Binary image without total vegetation and small objects like stone

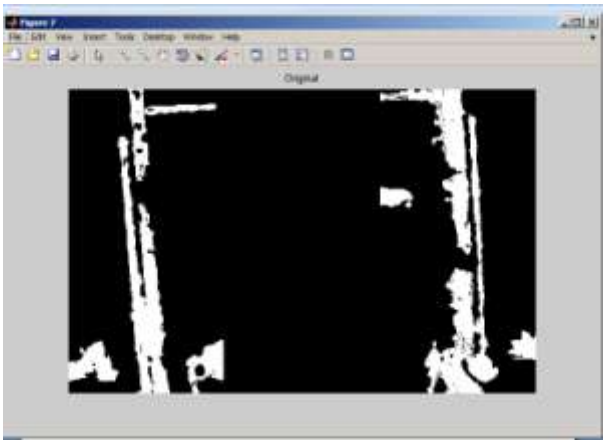

Figure 3.20: Image after dilating the image vertically

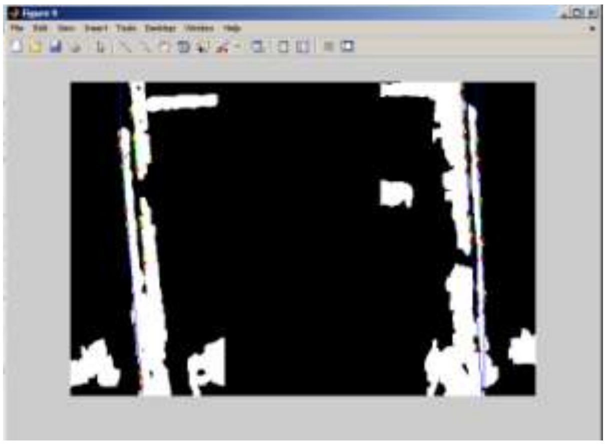

Figure 3.21: Detected full line by Hough transform and interpolation

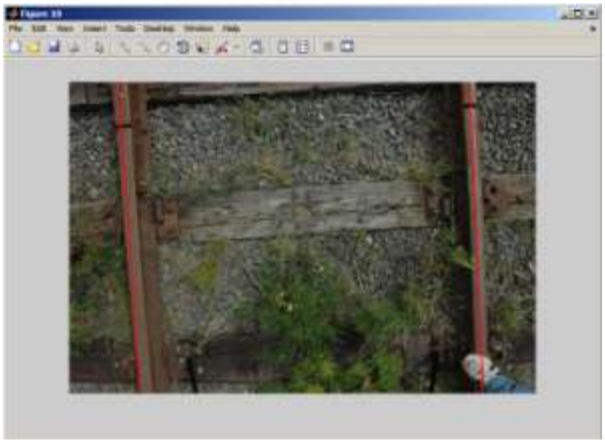

Figure 3.22 : Detected line in original RGB image

3.5 Detecting the sleeper

After detecting the rail, we remove the rail from the picture then we detect the sleeper by using texture segmentation by entropy filter. Then we detect the centroids of the sleepers by region properties function in binary image. After that we drew a perpendicular line from the centroids to each slipper. Sometimes, sleepers are totally covered by vegetation. It is even difficult for human eyes to detect the sleepers. It seems that there is no sleeper on the rail line. If no centroids is found on the image assume them which means assume the sleepers. If the row wise distance of the centroids are less than 70 which means they belongs to the same slipper, average then and make sure that one centroids for one sleepers. If the column wise distance of the centroids are greater than 190 then put a centroids between them which means assume a new sleeper between then.

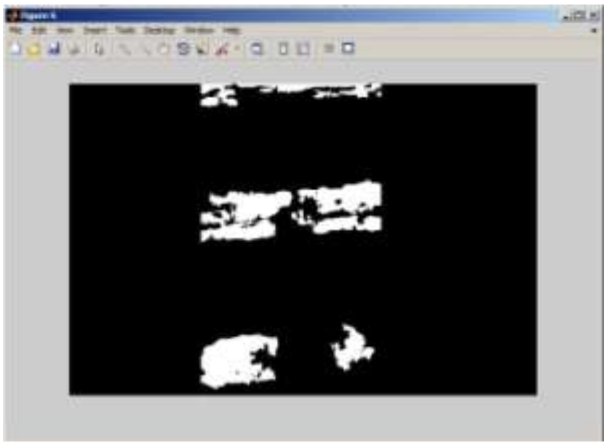

Figure 3.23: Detected sleeper in binary image after removing the rail line from the image

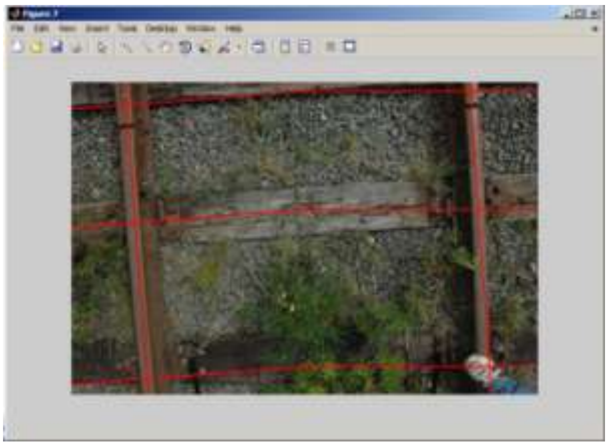

Figure 3.24: Detected both line and sleeper in original image

RESULT AND ANALYSIS

4.1 ANALYSIS OF VEGETATION SEGMENTATION

There are some problems in measuring the accuracy of the detected vegetation such as

1) Comparing our result with the Rail way vegetation expert's one. In this case, the Rail way vegetation expert is not available.
2) Some vegetation are very small and sometime the light condition is so bad that even it is very difficult for human eye to find out which portion is vegetation and which one is not from the image.
3) There is a lack of standard scale to measure the accuracy of the detected vegetation

To test the performance of the vegetation segmentation, we manually assigned over 50 vegetation regions and manmade objects regions in different images where it is clear that there are only vegetation regions or manmade objects regions. This assessment technique was previously used in other researches [1].
The performance of the vegetation segmentation technique is assessed by using two measures denoted as "detection ratio" and "false detection ratio". The detection ratio is the ratio of rightly detected pixels within the allocated vegetation regions to the total number of pixels within the allocated vegetation regions. The false detection ratio is defined analogously.

Some assigned vegetation regions and their corresponding vegetation detection results are given in Appendix-C (Page 57).

The average vegetation detection ratio is 90.87 % of the vegetated image regions. On an average only 0.43 % manmade object pixels are falsely classified as vegetation pixels.

4.2 ANALYSIS OF RGB COLOR MODEL IMAGE

4.2.1 Advantages of RGB

Extracting the vegetation in RGB by Green color priority can segment most of the vegetation in RGB color space. The RGB color model is the most widespread chosen for the computer graphics as color displays use red, green, and blue to create the expected color. For that reason, Choosing the RGB color model simplifies the both the architecture and the design of the system. Also, the system which is designed by using the RGB color model can take advantage on a large number of existing software routines, because this color model has been around for a number of years [7].

4.2.2 Problems with RGB Color Space

But extracting the vegetation in RGB by Green priority technique we face some problems, for example

1) if the green color is near to white for high light reflection.
2) if the green color is near to black for very low light condition and
3) it cannot detect deep brown vegetation by green priority technique.

Conversely, RGB color space is not very efficient when dealing with the “real-world” images. All three RGB components require to be of equal bandwidth to generate any color within the RGB color cube. The outcome of this is a frame buffer which has the same pixel depth and display resolution for each RGB component. Moreover, processing an image in the RGB color space is usually not the most capable method. For instance, to modify the intensity or color of a given pixel, the three RGB values must be read from the frame buffer, the intensity or color calculated, the desired modifications performed, and the new RGB values calculated and written back to the frame buffer. If the system had access to an image stored straightly in the intensity and color format, then some processing steps would be faster [7].

4.3 ANALYSIS OF HSV COLOR MODEL IMAGE

HSV color space was mainly used to extract the brown vegetation and overcome the limitations of the RGB color base vegetation segmentation. It was successfully able to detect the brown vegetation and also able to detect the green vegetation which was not detected in the first phase in RGB color space in high light reflection or for the low light condition. However, it has also a problem; it segments some of the brown part of the rusty iron rail and wood as vegetation which are not vegetation. They are comparatively very small.

4.3.1 Advantages of converting to HSV

HSV color model is similar to the human color perception which is not always in the case of RGB and CMYK (**c**yan, **m**agenta, **y**ellow, and **k**ey (black).). In other color model, colors are defined in the relation to the primary colors.

In the HSV color detection, Hue plays the central role since Hue is never change to the variations in the light conditions as its scale never change, shift invariant and never change under saturation changes.

HSV model is very helpful to solve the problems of Shadows and Highlights or the chromatic variation of day light [10]. For instance, a faded image can be considered as an image with low saturation; the saturation value of that image can be tuned of that color as per the weather (day light) conditions. So, HSV color model is able to maintain the maximum information.

4.3.2 Problems with hue in HSV Color Space

The hue coordinate in HSV is unstable and also small changes in the RGB model causes strong variation in hue. It suffers from three problems as follows [10]:

The hue is meaningless when the intensity is very high or very low.
The hue is meaningless also when the saturation is very low.
And the hue becomes unstable when the saturation is less than the threshold value.

4.4 ANALYSIS OF SIZE FILTERS

4.4.1 Advantages of using size filter

During vegetation detection some part of the rail, wood, sleeper and stone is also detected as vegetation which is not vegetation. Almost all cases they are comparatively very small in size. Using the size filter after detecting the total vegetation, I am able to remove the noises from the total vegetation image and I get better result.

4.4.2 Disadvantages of using size filter

Though the size filter eliminate objects smaller than a single leaf, in some cases it also eliminate very small amount of vegetation from the picture. Because, the size filter is only considering the size of the objects neither color or texture. Size filter remove most of the error from the picture but not all.

4.5 Comparison with other vegetation detection algorithm:

We also tried to solve the distinguish problem between Vegetation and Manmade objects in three different ways:

1. Color and Texture segmentation
2. K-means color segmentation
3. Color and Texture segmentation by using SVM

4.5.1 Color and Texture segmentation

In this approach first we extract the green vegetation from the input image by color segmentation in both RGB and HSV color space by green priority in RGB and thresholding in H and V values in HSV. Then we remove the rail and sleeper by range filter (texture segmentation) in different color space of CMYK. After removing the rail and sleepers, we remove the small object like stone from the picture by size filter. Then we detect the brown vegetation by color segmentation in HSV color space. Finally, we add up both the vegetation image such as green vegetation and brown vegetation. This approach gave me the best result for vegetation detection but it is very slow. It takes 20 to 22 seconds for detecting vegetation only in 400 x 600 pixels image on an ordinary laptop computer with a 1.60 GHz AMD E-350 Processor, RAM 4 GB (3.60 useable), Windows 7 Home Premium, MATHLAB Version 7.10.0.499(R2010a).

4.5.2 K-means color segmentation

In this approach we try to detect the vegetation by K-means color segmentation where first we need to fix the number of clusters for color segmentation. Different number of clusters were tried. It did not work for vegetation detection. There were mainly two reasons for that. First, in different light condition and different weather situation and in different day time the same vegetation has a wide range of colors. The fixed number of cluster works for some images but not for all. Second, problems with detecting brown vegetation because some part of the rail and wooden sleeper are also brown which goes to the same clusters.

4.5.3 Color and Texture segmentation by using SVM

In this approach a SVM is used to classify the Vegetation and Manmade objects from the image. Where the SVM is applied with both color and texture features then in the testing phase the image objects are classified in to two groups by different convolutions mix size. But the classification results were so poor and also this approach is very slow. A hybrided version of this approach was also applied with color segmentation by green priority in RGB. But it did not give good result either.

4.6 Analysis of rail line detection

Accuracy can be defined as a statistical measure of how well an algorithm correctly detects or exclude a condition, as defined in the following:

$$\text{Accuracy} = \frac{\text{number of True Positive} + \text{ number of False Negative}}{\text{number of True Positive} + \text{ False Positive } + \text{False Negative} + \text{ True Negative}}$$

$$\text{Precision} = \frac{\text{number of True Positive}}{\text{number of True Positive} + \text{ False Positive}}$$

The detection speed is defined as, the time required for an algorithm to generate the detection results since it obtain the input image. The proposed algorithm was evaluated by 87 images. The table 1 shows the analysis of experiment that was conducted by using 87 images.

Table 1: Analysis of experiment for rail line detection

Image Name	True positives (actual Rail lines that were correctly classified as Rail lines)	False negatives (Rail lines that were incorrectly marked as non-rail lines)	False positives (non-rail lines that were incorrectly labeled as rail lines)	True negatives (all the remaining objects, correctly classified as non-rail lines)
_bjorbo 024	1	1	0	2
_bjorbo 025	2	0	0	2
_bjorbo 026	2	0	0	2
_bjorbo 027	2	0	0	2
_bjorbo 028	2	0	0	2
_bjorbo 029	2	0	0	2
_bjorbo 030	2	0	0	3
_bjorbo 031	2	0	0	2
_bjorbo 032	2	0	0	2
_bjorbo 033	2	0	0	2
_bjorbo 034	2	0	0	2
_bjorbo 035	2	0	0	3
_bjorbo 036	2	0	0	2
_bjorbo 037	2	0	0	2
_bjorbo 038	2	0	0	2
_bjorbo 039	2	0	0	2
_bjorbo 040	2	0	0	2
_bjorbo 041	2	0	0	2
_bjorbo 042	2	0	0	2
_bjorbo 043	2	0	0	2
_bjorbo 044	2	0	0	2
_bjorbo 045	2	0	0	2
_bjorbo 046	2	0	0	2
_bjorbo 047	2	0	0	3

_bjorbo 048	2	0	0	3
_bjorbo 049	2	0	0	3
_bjorbo 050	2	0	0	3
_bjorbo 051	2	0	0	3
_bjorbo 052	2	0	0	3
_bjorbo 053	2	0	0	3
_bjorbo 054	2	0	0	3
DSC_0024	2	0	0	2
DSC_0025	2	0	0	2
DSC_0026	2	0	0	2
DSC_0027	2	0	0	2
DSC_0028	2	0	0	2
DSC_0029	2	0	0	2
DSC_0030	2	0	0	2
DSC_0031	2	0	0	2
DSC_0032	2	0	0	2
DSC_0033	2	0	0	2
DSC_0034	2	0	0	2
DSC_0035	1	1	0	2
DSC_0036	2	0	0	2
DSC_0037	2	0	0	2
DSC_0038	2	0	0	2
DSC_0039	1	1	0	3
DSC_0040	2	0	0	2
DSC_0041	2	0	0	3
DSC_0042	1	1	0	3
DSC_0043	2	0	0	2
DSC_0044	2	0	0	2
DSC_0045	1	1	0	2
DSC_0046	2	0	0	2
DSC_0047	2	0	0	2
DSC_0048	2	0	0	2
DSC_0049	2	0	0	2
DSC_0050	1	1	0	2
DSC_0051	2	0	0	2
DSC_0052	2	0	0	2
DSC_0053	2	0	0	2
DSC_0054	2	0	0	2
DSC_0055	2	0	0	2
DSC_0056	2	0	0	2
DSC_0057	2	0	0	2
DSC_0058	2	0	0	3
DSC_0059	1	1	0	2

DSC_0060	2	0	0	3
DSC_0061	2	0	0	2
DSC_0062	2	0	0	2
DSC_0063	2	0	0	2
DSC_0064	2	0	0	2
DSC_0065	2	0	0	2
DSC_0066	2	0	0	2
DSC_0067	2	0	0	2
DSC_0068	2	0	0	2
DSC_0069	2	0	0	2
DSC_0070	2	0	0	2
DSC_0071	1	1	0	2
DSC_0072	2	0	0	2
DSC_0073	1	1	0	3
DSC_0074	1	1	0	3
DSC_0075	2	0	0	3
DSC_0076	2	0	0	2
DSC_0077	1	1	0	3
DSC_0078	1	1	0	3
DSC_0079	2	0	0	3
Total	TP = 162	FN = 12	FP = 0	TN =195

It should be noted that the results of detection into different classes (true positives, false negative, false positives and true negatives) in the table below are based on manual observation i.e. rails detected by the algorithm are placed on the actual image to validate detection.

Table 2: Confusion matrix for Rail line detection

True positives (actual Rail lines that were correctly classified as Rail lines) TP = 162	False negatives (Rail lines that were incorrectly marked as non-rail lines) FN = 12
False positives (non-rail lines that were incorrectly labeled as rail lines) FP = 0	True negatives (all the remaining objects, correctly classified as non-rail lines) TN =195

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

where, TP denotes True Positive, FP denotes False Positive , FN denotes False Negative and TN denotes True Negative.

$$\text{Accuracy} = \frac{162 + 195}{162 + 0 + 12 + 195}$$

$$\text{Accuracy} = \frac{357}{369}$$

$$\text{Accuracy} = 0.967479$$

The total accuracy of rail line detection by the system for the 87 images was taken = 96.75%

Likewise, Precision establishes the proportion of the correct instances of cases that were predicted positive.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Precision} = \frac{162}{162 + 0}$$

$$\text{Precision} = 1$$

This means the precision rate of rail line detection for the 87 images is 100 %

4.7 Limitation of the approach for rail line detection:

In this work the position of the rail line measured by mainly considering Hough transform where we considered that the rail lines are straight. It gives 96.75% accuracy for all the 87 images in natural light condition where the rail lines are assumed straight. But in really rail lines are not always straight. In the sudden tearing point and in the junction the rail lines are not straight. In such a situation my system cannot give an effective result.

4.8Advantages of using Hough Transform

The advantage of the Hough transform for detecting straight line is that all the pixels lying on one line do not needed to be contiguous which is very useful for detecting lines with short breaks in them due to noise, or when objects are partially occluded [9].

4.9 Disadvantages of using Hough Transform

One of the disadvantages of the Hough transform is that it can provide misleading results when objects happen to be aligned by chance. This clearly illustrates another disadvantage which is that the detected lines are infinite lines described by their (m,c) values, rather than the finite lines with the defined end points [9].

4.10 Analysis of the Sleeper detection

It should be noted that the results of detection into different classes (true positives, false negative, false positives and true negatives) in the table below are based on manual observation i.e. Sleepers detected by the algorithm are placed on the actual image to validate detection.

Table 3: Analysis of experiment for sleeper detection

Image Name	True positives (actual Sleeper that were correctly classified as Sleeper)	False negatives (Sleeper that were incorrectly marked as non-Sleeper)	False positives (non-Sleeper that were incorrectly labeled as Sleeper)	True negatives (all the remaining objects, correctly classified as non-Sleeper)
_bjorbo 024	2	0	0	1
_bjorbo 025	2	0	1	2
_bjorbo 026	2	0	1	2
_bjorbo 027	2	0	0	2
_bjorbo 028	2	1	1	2
_bjorbo 029	2	1	1	2
_bjorbo 030	3	0	0	2
_bjorbo 031	2	0	0	2
_bjorbo 032	2	0	0	2
_bjorbo 033	2	0	0	2
_bjorbo 034	2	0	0	2
_bjorbo 035	3	0	0	2
_bjorbo 036	2	0	0	2
_bjorbo 037	2	0	0	2
_bjorbo 038	2	0	0	2
_bjorbo 039	2	0	0	2
_bjorbo 040	2	0	0	2
_bjorbo 041	2	0	1	2
_bjorbo 042	2	0	0	2
_bjorbo 043	2	0	0	2
_bjorbo 044	2	0	0	2
_bjorbo 045	2	0	0	2
_bjorbo 046	2	0	0	2
_bjorbo 047	3	0	0	2
_bjorbo 048	3	0	0	2
_bjorbo 049	3	0	0	2

_bjorbo 050	3	0	0	2
_bjorbo 051	3	0	0	2
_bjorbo 052	3	0	0	2
_bjorbo 053	3	0	0	2
_bjorbo 054	3	0	0	2
DSC_0024	2	0	1	2
DSC_0025	2	0	1	2
DSC_0026	2	0	0	2
DSC_0027	2	0	0	2
DSC_0028	2	0	0	2
DSC_0029	2	0	0	2
DSC_0030	2	0	1	2
DSC_0031	2	0	1	2
DSC_0032	2	0	0	2
DSC_0033	2	0	0	2
DSC_0034	2	0	0	2
DSC_0035	2	0	0	1
DSC_0036	2	0	0	2
DSC_0037	2	0	0	2
DSC_0038	2	0	0	2
DSC_0039	3	0	0	1
DSC_0040	2	0	0	2
DSC_0041	3	0	0	2
DSC_0042	3	0	0	1
DSC_0043	2	0	0	2
DSC_0044	2	0	0	2
DSC_0045	2	0	0	1
DSC_0046	2	0	0	2
DSC_0047	2	0	0	2
DSC_0048	2	0	0	2
DSC_0049	2	0	0	2
DSC_0050	2	0	0	1
DSC_0051	2	0	0	2
DSC_0052	2	0	0	2
DSC_0053	2	0	0	2
DSC_0054	2	0	0	2
DSC_0055	2	0	0	2
DSC_0056	2	0	0	2
DSC_0057	2	0	0	2
DSC_0058	3	0	0	2
DSC_0059	2	0	0	1
DSC_0060	3	0	1	2
DSC_0061	2	0	0	2

DSC_0062	2	0	1	2
DSC_0063	2	0	0	2
DSC_0064	2	0	0	2
DSC_0065	2	0	0	2
DSC_0066	2	0	0	2
DSC_0067	2	0	0	2
DSC_0068	2	0	0	2
DSC_0069	2	0	0	2
DSC_0070	2	0	0	2
DSC_0071	2	0	0	1
DSC_0072	2	0	0	2
DSC_0073	3	0	0	1
DSC_0074	3	0	0	1
DSC_0075	3	0	0	2
DSC_0076	2	0	0	2
DSC_0077	3	0	1	1
DSC_0078	3	0	1	1
DSC_0079	3	0	0	2
Total	TP = 195	FN = 2	FP = 13	TN = 162

Table 4: Confusion matrix for Sleepers detection

True positives (actual sleepers that were correctly classified as Sleepers) TP = 195	False negatives (Sleepers that were incorrectly marked as non-sleeper) FN = 2
False positives (non-sleeper that were incorrectly labeled as sleeper) FP = 13	True negatives (all the remaining objects, correctly classified as non-sleeper) TN = 162

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

$$\text{Accuracy} = \frac{195 + 162}{195 + 13 + 2 + 162}$$

$$\text{Accuracy} = \frac{357}{372}$$

$$\text{Accuracy} = 0.959677$$

The total accuracy of Sleeper detection by this system for the 87 images was taken = 95.97%

Similarly, Precision find outs the proportion of the correct instances of cases that were predicted positive.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{or Precision} = \frac{195}{195 + 13}$$

$$\text{or Precision} = \frac{195}{208}$$

$$\text{or Precision} = 0.9375$$

This means the precision rate of sleepers' detection for the 87 images is 93.75 %

CONCLUSION AND FUTURE WORKS

5.1 Conclusion

The objective of this thesis work was to develop an algorithm to classify Vegetation and Man-made objects on the railway tracks and then measure the amount of Vegetation between each pair of sleepers with high speed. The Vegetation was detected in two phases. The vegetation detection in RGB color space by considering the green priority was able to detect most of the green and near to green vegetation in good weather condition. The remaining vegetation, especially brown vegetation was detected even also in bad light condition from the image in HSV color space by considering the 'Hue' value with different values of 'Value'. The sleeper positions are detected by texture segmentation, e.g. by entropy filtering, with 93.75% accuracy and also assumed with respect to the rail line position, if the sleeper was totally covered by vegetation. The rail line position was detected by Hough Transform and interpolation function with 96.75 % accuracy. The system was tested on 87 images of natural light condition and the execution time for each image was calculated in between 5.765 sec to 6.534 sec for image size 400x600 pixels on an ordinary laptop computer with a 1.60 GHz AMD E-350 Processor, RAM 4 GB (3.60 useable), Windows 7 Home Premium, MATHLAB Version 7.10.0.499(R2010a). The system correctly detects vegetation in 90.87 % of the vegetated image regions. Only 0.43 % of the manmade objects pixels are falsely classified as vegetation. I also applied the vegetation detection part for detecting vegetation on different type of images like forest or garden and it shows excellent performance and robustness.

5.2 Future Works

In recognition process, Image Segmentation is the most critical part. More robust segmentation is needed there. For that the following can be considered as the possible future works

1. If we apply fuzzyfication techniques to the HSC color model parameters (hue, saturation and value parameters), which could be adaptable to the different weather conditions and could be tuned according to the situations then it is likely to be more robust and we might get better accuracy.

2. For vegetation detection if we perform spectral analysis in RGB color space as well as VIS-NIR (visible / near-infrared spectrum) then we might get better result. Because in RGB analysis it is considered as a fact that chlorophyll appears green within the visible spectrum.
In the near-infrared spectrum, objects which contain chlorophyll have high reflectance than in the visible spectrum. Note that the NIR reflectance of vegetation containing chlorophyll is 4 to 7 times higher than its reflectance at the green-peak [1] [8].

3. For far better accurate result, we can couple our system with other sensors like thermal sensor, metal detector. By using a metal detector we can eliminate Man- made metallic objects e.g., like iron rail, base plate, etc. from the original image . In present though the proposed system is giving good result but still some very small part of the metal rail track is in the vegetation segments. If we couple a metal detector with the proposed system then we will get better result. Another thing is we know that in nature living organism has more temperature than inanimate objects. Therefore, if we couple our system with a thermal sensor than we may also get better result.

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Appendix-A

Table 5: Image Sources

Sl. No.	Figure name	Image sources
Figure 2.1	A saturation/value slice of a specific hue in the HSV model	http://www.ncsu.edu/scivis/lessons/colormodels/color_models2.html
Figure 2.2	Example saturation and value variations on a single red hue	http://www.ncsu.edu/scivis/lessons/colormodels/color_models2.html
Figure 2.3	HSV color model	https://sites.google.com/site/sachidanandabs/colorspace
Figure 3.9	HSV color model	http://www.blackice.com/colorspaceHSV.htm
Figure 8.2.1		http://www.ehow.com/facts_7236232_leaves-pear-tree-turning-yellow_.html
Figure 8.4.1 ; Figure 8.5.1; Figure 8.6.1; Figure 8.7.1		http://fallgetaways.iloveny.com/LANDING_LEAF_IDENTIFIER.html
Figure 8.3.1		http://www.normankoren.com/light_color.html
Figure 8.11.1		http://www.ehow.com/info_8094654_tree-leaves-turning-yellow.html
Figure 8.12.1		http://www.free-wallpapers-free.com/preview/yellow-leaf-tree-2/
Figure 8.10.1		http://www.123rf.com/photo_7376395_bright-yellow-flowers-of-the-forsythia-tree--useful-as-a-background.html
Thanks to Mr. Roger Nyberg for providing me the railway tracks pictures for my thesis work, which were taken by him.		

A.1 Extracting the vegetation in RGB by Green priority

Pseudocode
Begin
Get the RGB image
For every pixel calculate ExG = 2G-R-B
For every pixel if ExG >27
Then it is Vegetation
End

A.2 Extracting the vegetation in HSV color space by thrasholding

Pseudocode
Begin
Get the RGB image after extracting the ExG green
Convert the RGB image to HSV image
For every pixel if Hue < 150 AND Hue > 50 AND Value>.12 (Value>.12 is to avoid the color which is near to black)
For every pixel if Hue < 51 AND Hue > 45 AND Value>.12 (Value>.15 is to avoid the color which is near to black)
Then it is Vegetation (Color of the vegetation)
End

A.3 Implementation Of Size Filter

Pseudocode
Begin
Read the RGB image of Total Vegetation
Convert the image into binary image
Cheak the area of each object
if area of the object >30 pixel
then Vegetation
else Man Made Object
End

After calculating the total vegetation we post process the image then we go for detecting the rail lines by texture segmentation.

A.4 Post processing the image

Pseudocode

Begin
Accept RGB image
Convert the original RGB image into Gray image
Process the image by imadjust & histeq
Cheak the gray level value of each pixel
if the gray level value of the pixel < Average gray level value of the whole image
then New pixel value = Old pixel value+(average gray level value /1.75).
else Old pixel value
End

A.5 Rail line detection

Pseudocode

Begin
Accept the Gray level image
Use entropy filter to get the local entropy of the gray scale image
Convert the image into binary image
do logical NOT operations
Convert the Total Vegetation image into binary image
Remove the vegetation from the total image. ImageWithOutvegetation=Original image – Total Vegetation image
Remove all the objects from the image which are less than 700 Pixels
Do dilation operation vertically (90) on the image
Use hough, houghpeaks and hough line function respectively for detecting line
Use the both theta value & interp1 function to get the beginning and the end point of the full line which are perpendicular to the base
Draw all full lines from top to bottom of the pictures
Find the average of top left, top right beginning point and fine the bottom left and bottom right of the end point of those lines
Draw two lines from two pair of points for left rail and right rail
End

A.6 Sleeper Detection

Pseudocod

Begin
After detecting the rail, remove the rail from the picture
So we have only the picture of sleeper, do dilation operation of the picture
Find the centroids of each objects which means find the centroids of detected slippers
If the is no centroids on the image assume them which means assume the slipper
if the row wise distance of the centroids are less than 70 which means they belongs to the same slipper, average then and one centroids for one slipper
if the column wise distance of the centroids are greater than 190 then put a centroids between them which means assume a new sleeper between then
End

Appendix-B

Color and Texture segmentation

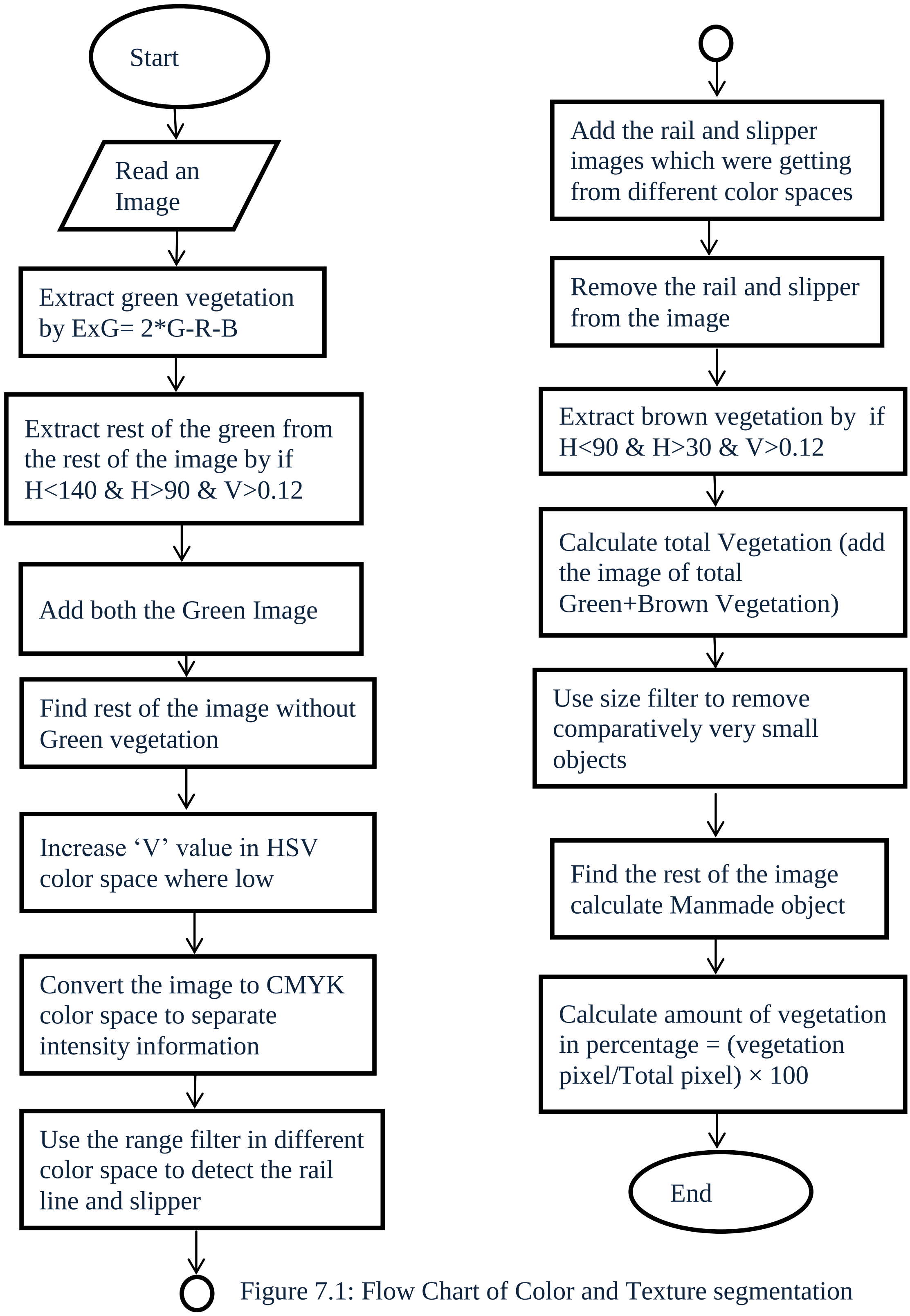
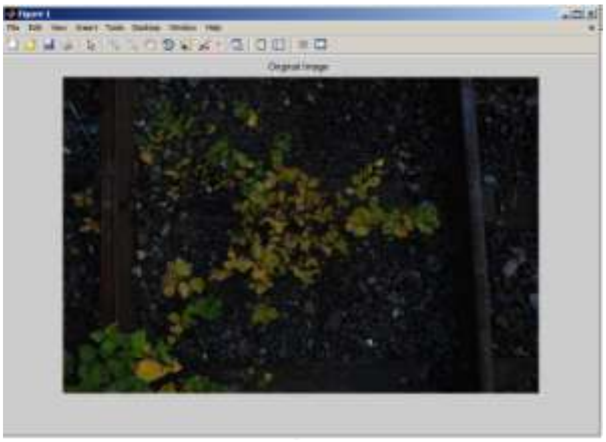
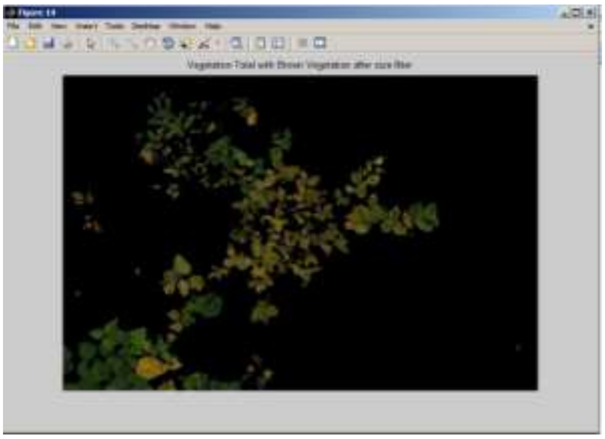
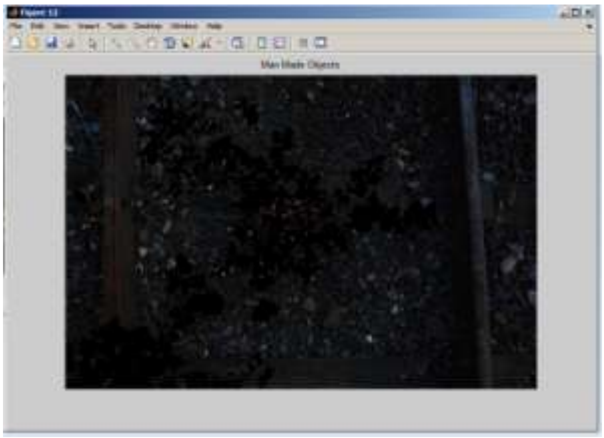


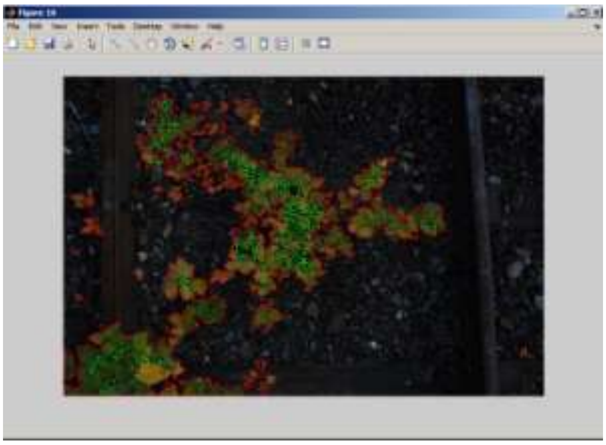
Figure 7.1: Flow Chart of Color and Texture segmentation

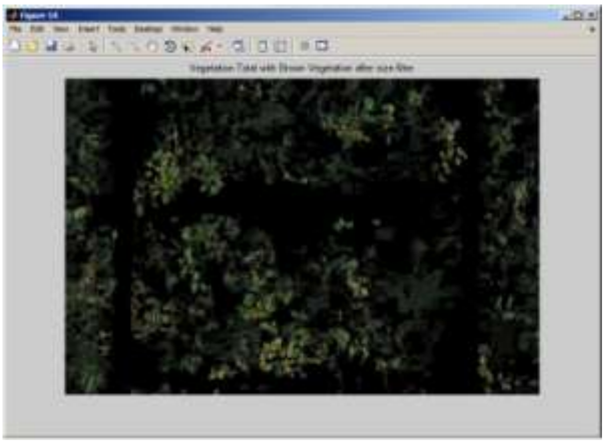
Some outputs of Color and Texture segmentation

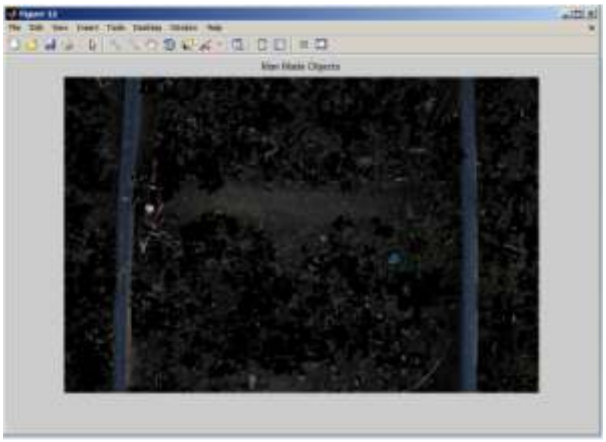


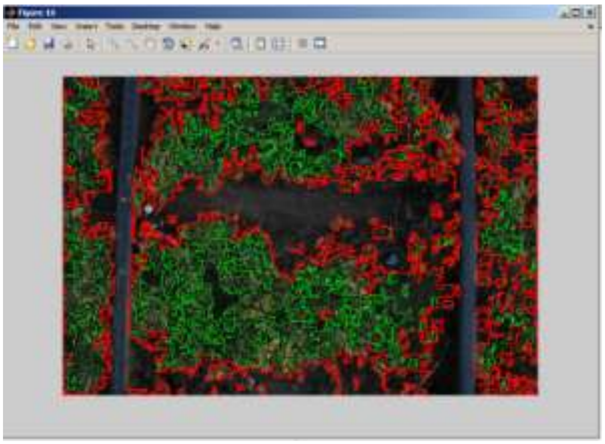


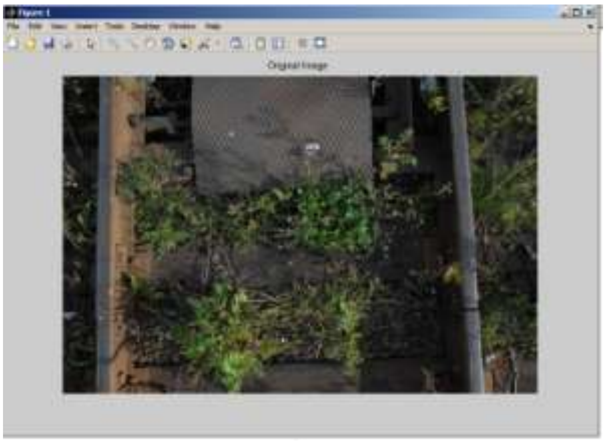


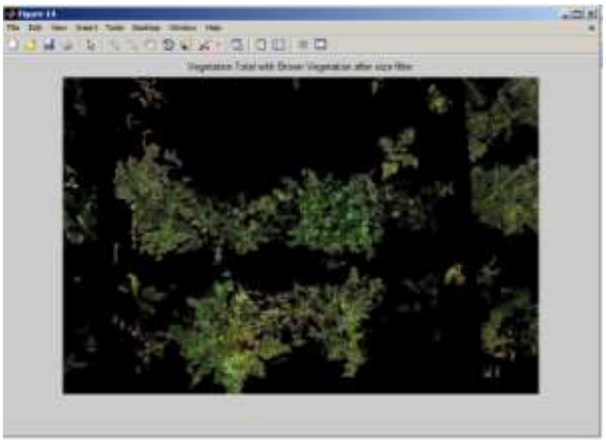


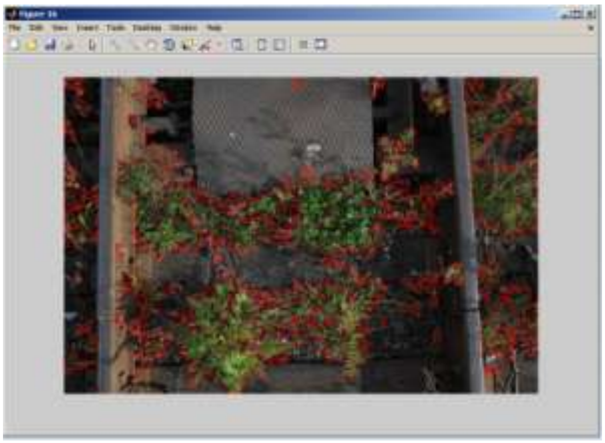












K-means color segmentation

In this approach we tried to detect the vegetation by K-means color segmentation where first we need to fixed the number of clusters for color segmentation. The fixed number of cluster works for green vegetation in some images but not for all. Another reason was brown vegetation because some part of the rail and wooden sleeper are also brown which goes to the same clusters.

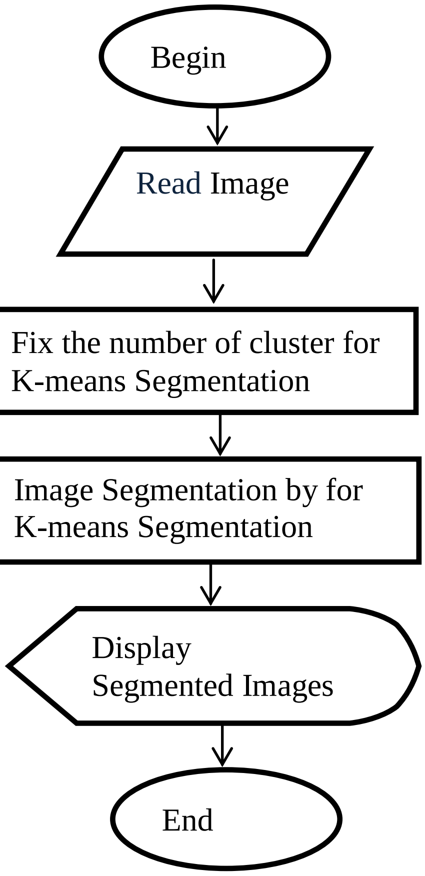
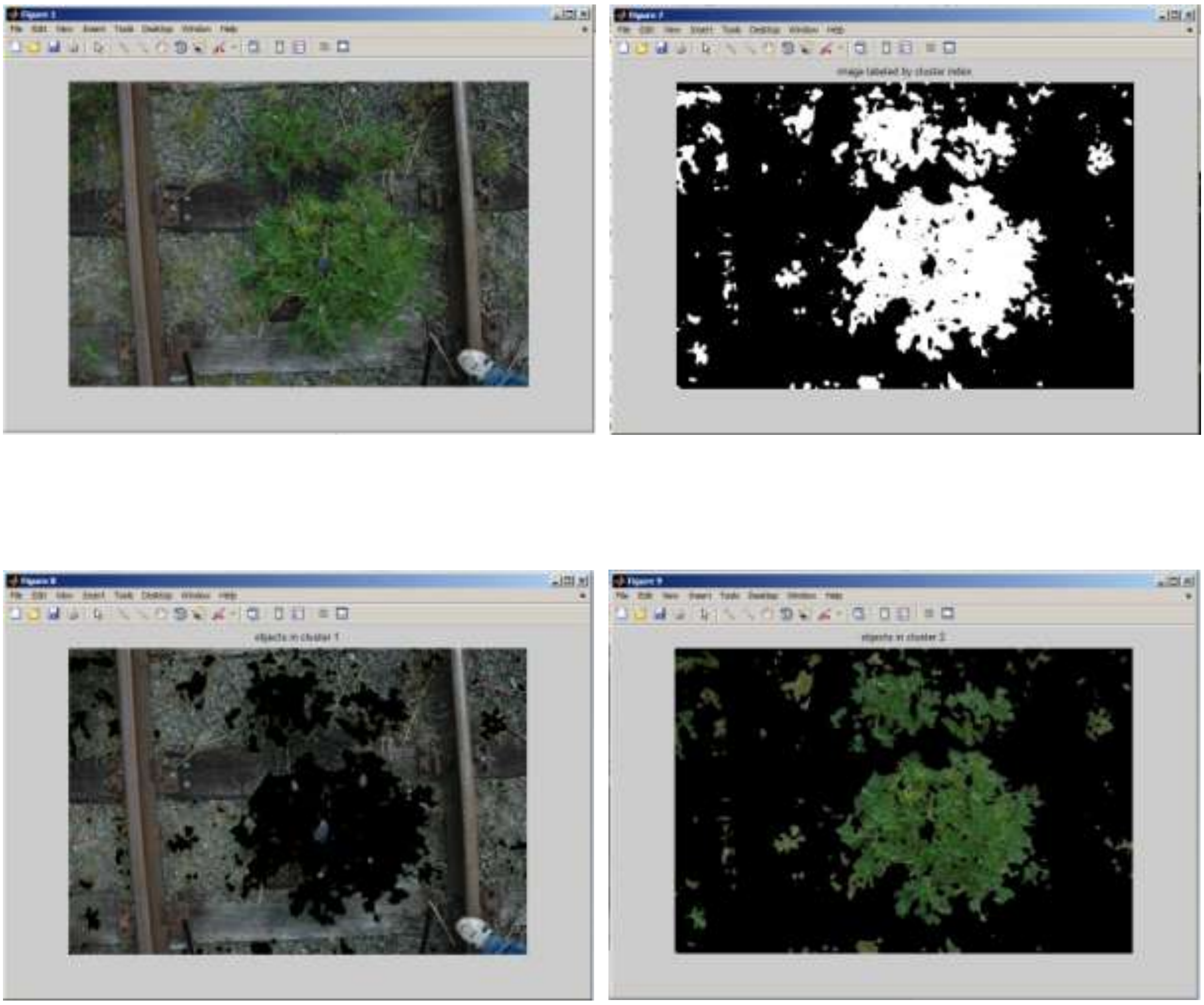
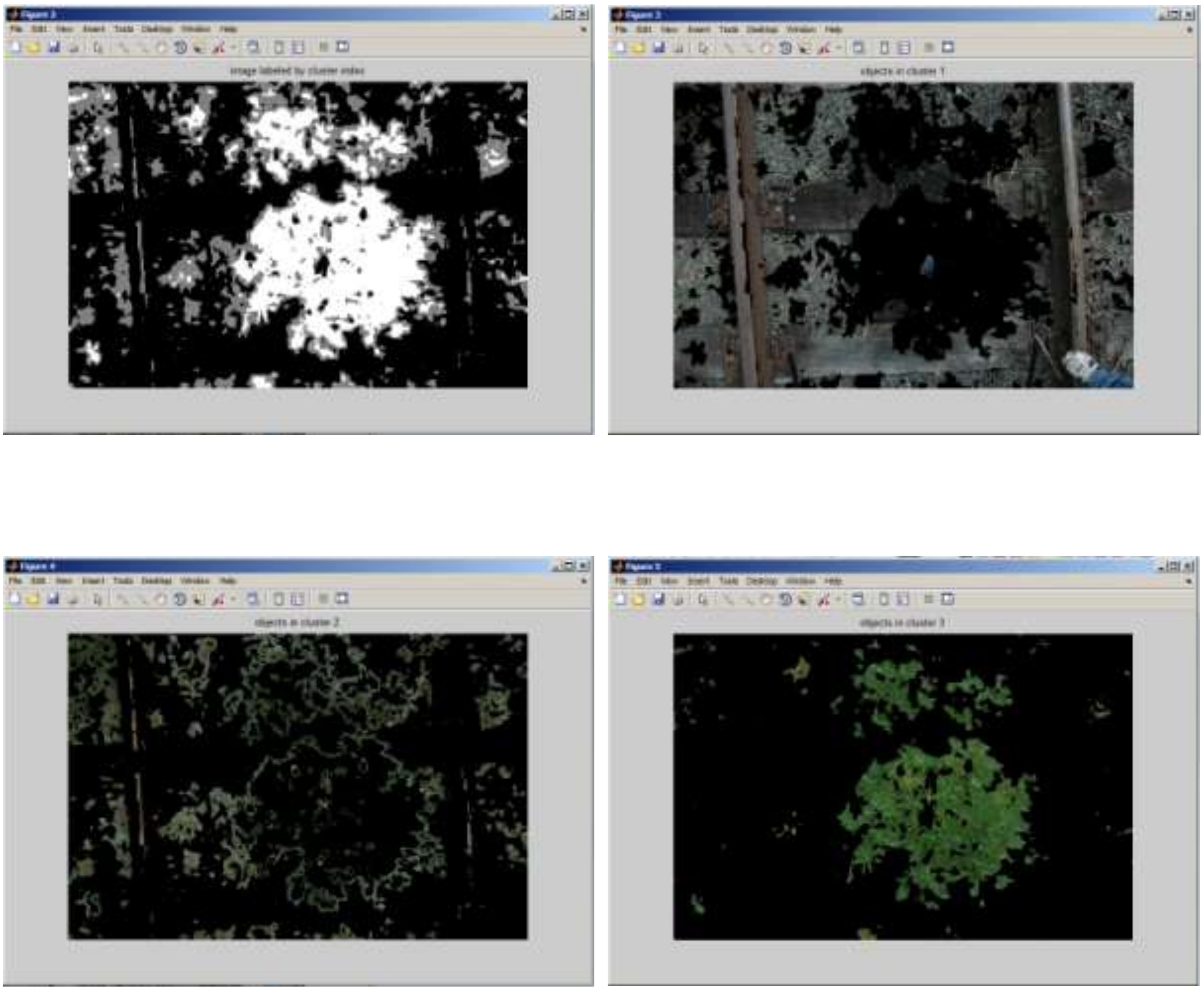


Figure 7.2: Flow Chart of K-means color segmentation

Output of K-means color segmentation for two clusters



Output of K-means color segmentation for three clusters on the same image



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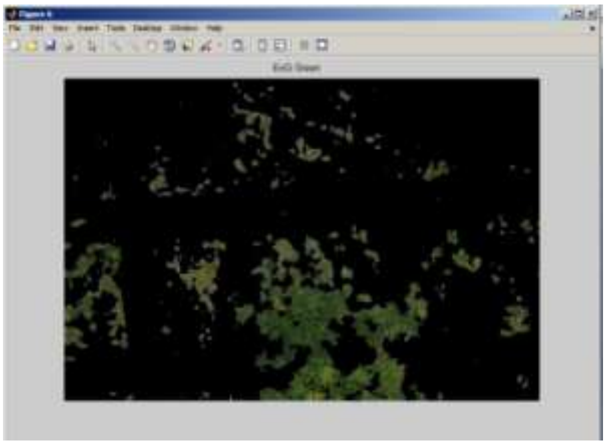
Color and Texture segmentation by using SVM

In this approach a SVM was used to classify the Vegetation and Manmade objects from the image. First, we trained the SVM by both color and texture features then in the testing phase we tried to classify the image objects in to two classes by different convolutions mix size. Texture features were taken by gray level co-occurrence matrix .However, the classification results were so poor and also this approach is very slow. After hybriding this approach with color segmentation in RGB by green priority did not give good result either.

Figure 7.3: Samples of Vegetation 5x5 pixels:

Figure 7.4: Samples of Manmade 5x5 pixels:

Output of Color and Texture segmentation by using SVM



Appendix-C

C.1 The threshold for the Green priority segmentation technique in RGB has been determined through experimentation as 27 for all images.

In RGB color space, all colors are the combination of these three primary colors 'Red, Green and Blue'. In any green object such as Green Vegetation (and also near to green vegetation) the Green intensity of RGB color space is always greater than Red and Blue colors. So if we apply this formula on an image (G-R)+(G-B)=2*G-R-B, we will get a Gray Level image where all the objects color near to green will be in white with different intensities depending on the green values (more green will come more white) and all other objects which are not near to green will be black . A threshold is chosen as 27 through experimentation for all images to extract the vegetation where the green intensity is higher than red and blue color in RGB color space.

Some outputs of detected vegetation with different threshold values:

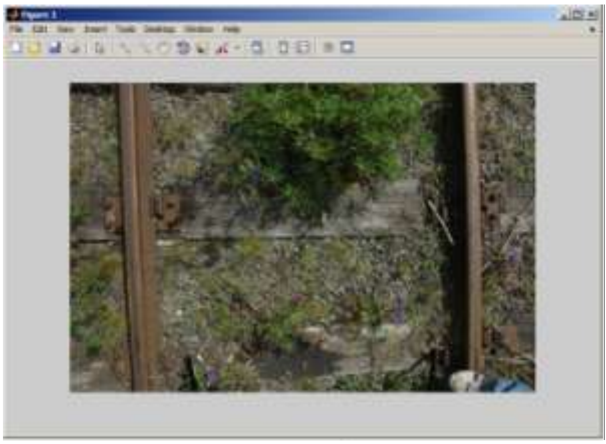


Figure 8.1.1: Original Image.

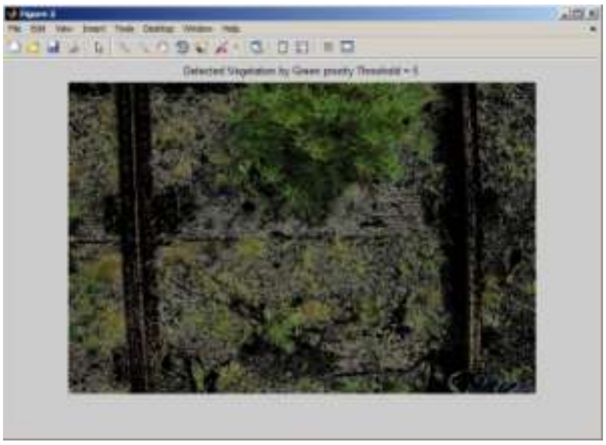


Figure 8.1.2: Detected Vegetation by Green priority where Threshold = 5.

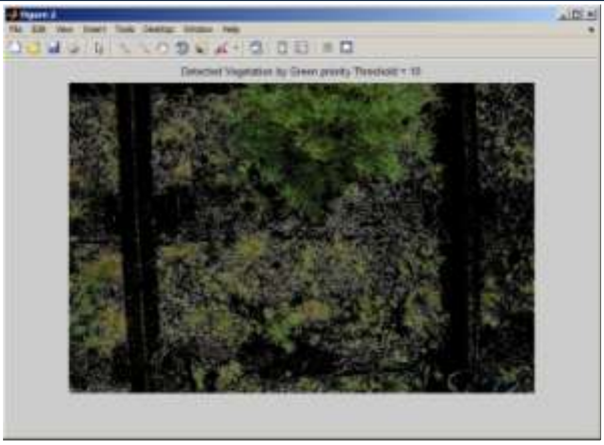


Figure 8.1.3: Detected Vegetation by Green priority where Threshold = 10.

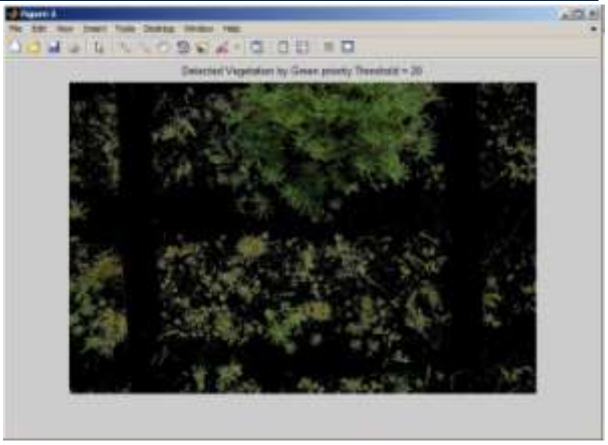


Figure 8.1.4: Detected Vegetation by Green priority where Threshold = 20.

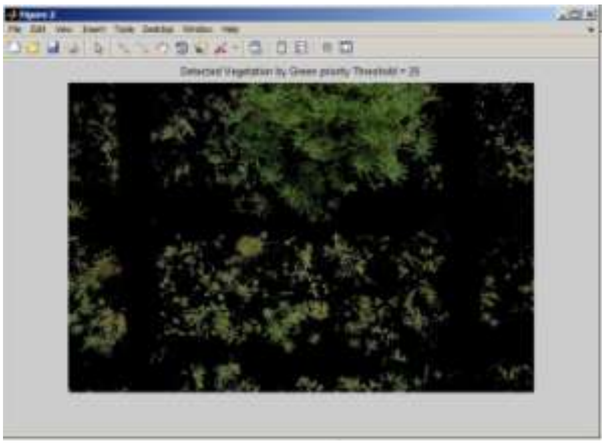


Figure 8.1.5: Detected Vegetation by Green priority where Threshold = 25.

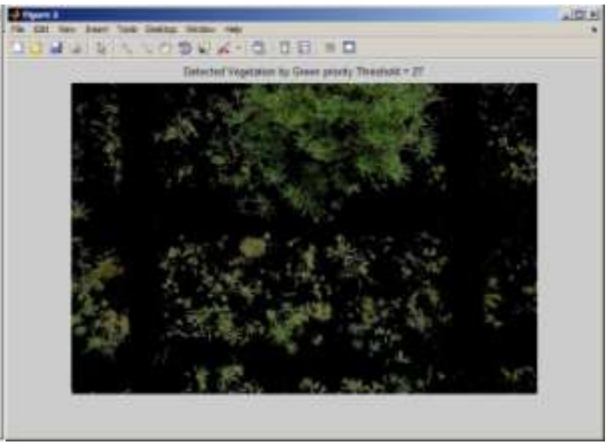


Figure 8.1.6: Detected Vegetation by Green priority where Threshold = 27.

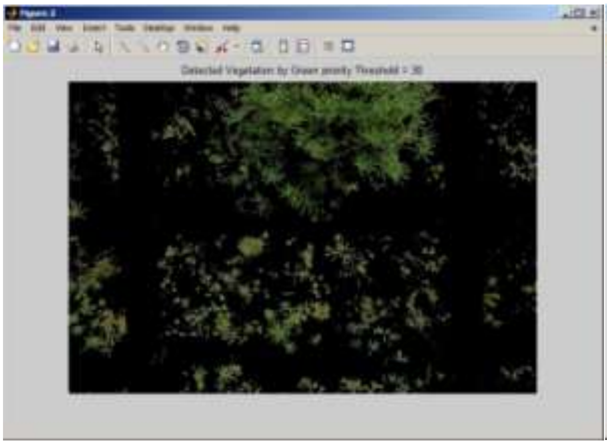


Figure 8.1.7: Detected Vegetation by Green priority where Threshold = 30.

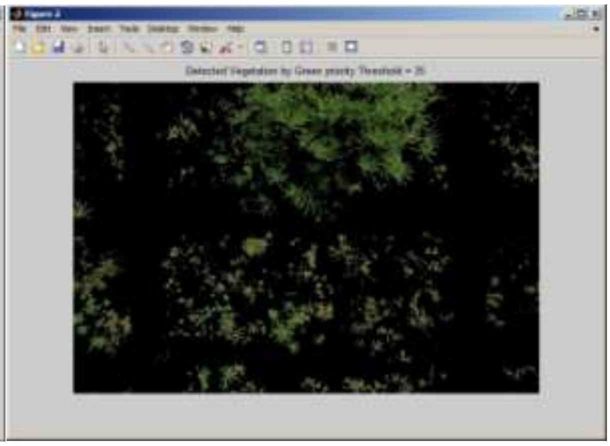


Figure 8.1.8: Detected Vegetation by Green priority where Threshold = 35.

Figure 8.1.9: Detected Vegetation by Green priority where Threshold = 40.

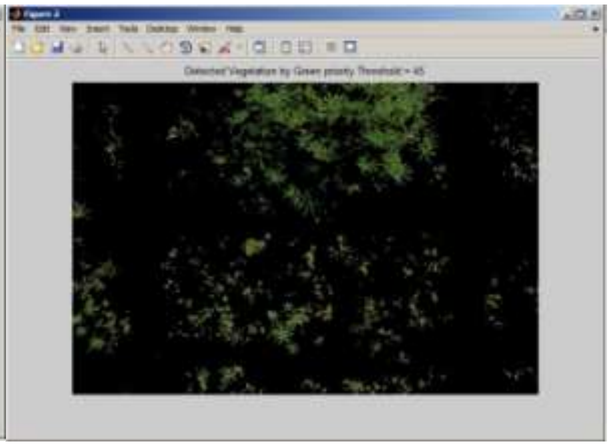


Figure 8.1.10: Detected Vegetation by Green priority where Threshold = 45.

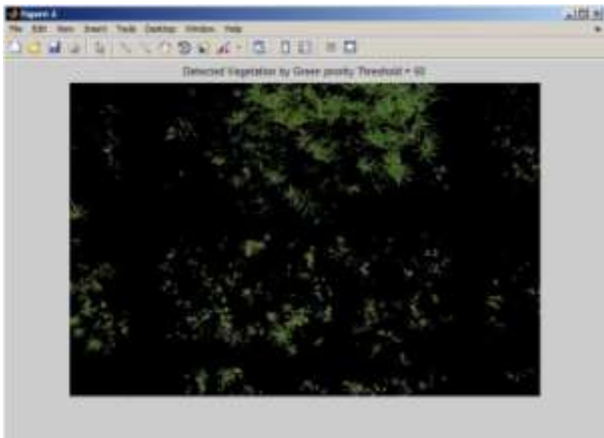


Figure 8.1.11: Detected Vegetation by Green priority where Threshold = 50.

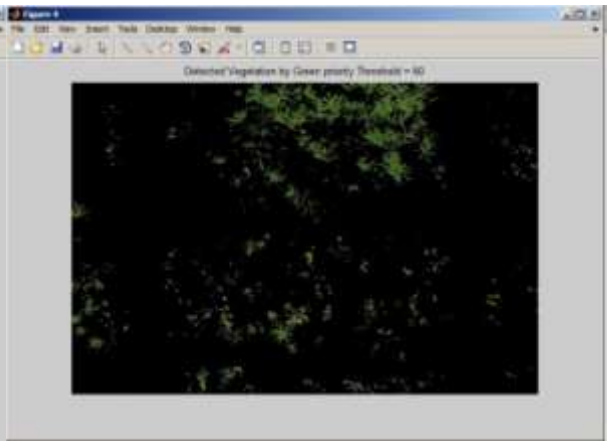


Figure 8.1.12: Detected Vegetation by Green priority where Threshold = 60.

C.2 Justification of combining the RGB and HSV color segmentation for vegetation detection

The combination of RGB and HSV color segmentation gives better result for vegetation detection. Both of these segmentation techniques have advantages and limitations . But each technique can overcome the limitations of another. For instance, in RGB green priority segmentation technique cannot detect the green
1) if the green color is near to white for high light reflection.
2) if the green color is near to black for very low light condition and
3) also, it cannot detect deep brown vegetation by green priority technique.

But these limitations can overcome by HSV color segmentation technique. HSV color segmentation technique can detect almost all the vegetation that could not be detected by the RGB technique. Similarly, the HSV technique also cannot detect some vegetation which can be detected by RGB technique.

In the images below , the first column are the Original Image, second image column are the pictures of detected vegetation in RGB green priority technique and the last image column are the pictures of detected vegetation in HSV color space. In the images RGB technique cannot detect some vegetation but the left vegetation are detected in HSV technique.

Figure 8.2.1: Original Image.

Figure 8.2.2: RGB Segmentation.

Figure 8.2.2: HSV Segmentation.

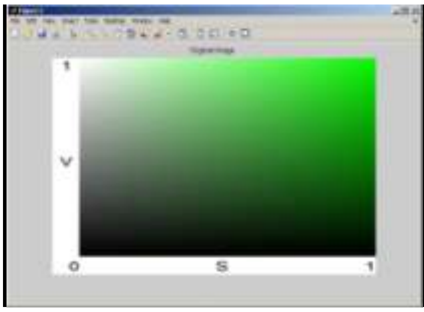


Figure 8.3.1: Original Image.

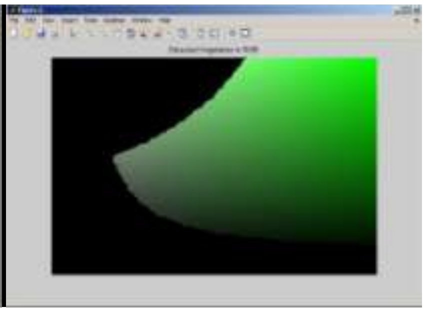


Figure 8.3.2: RGB Segmentation.

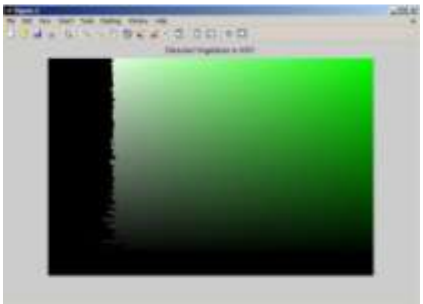


Figure 8.3.2: HSV Segmentation.

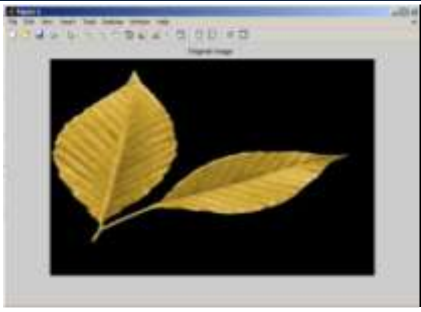


Figure 8.4.1: Original Image.


Figure 8.4.2: RGB Segmentation.


Figure 8.4.2: HSV Segmentation.

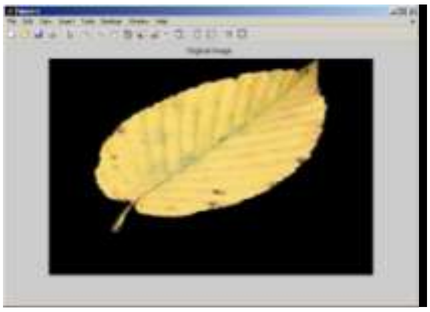


Figure 8.5.1: Original Image.

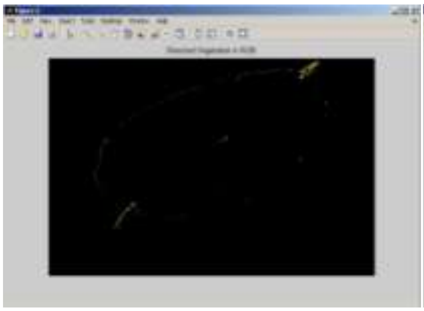


Figure 8.5.2: RGB Segmentation.

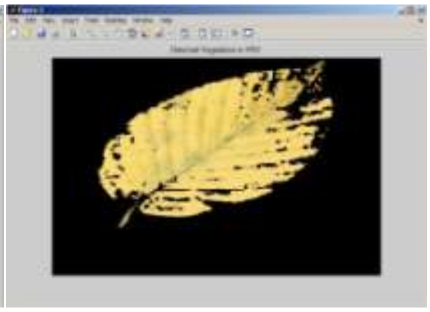


Figure 8.5.2: HSV Segmentation.


Figure 8.6.1: Original Image.


Figure 8.6.2: RGB Segmentation.

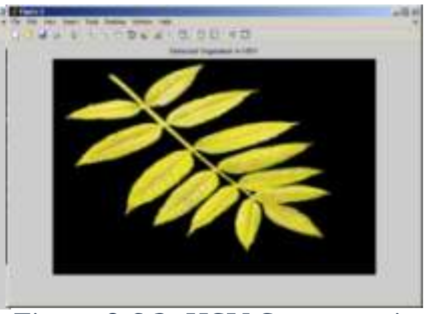


Figure 8.6.2: HSV Segmentation.


Figure 8.7.1: Original Image.


Figure 8.7.2: RGB Segmentation.

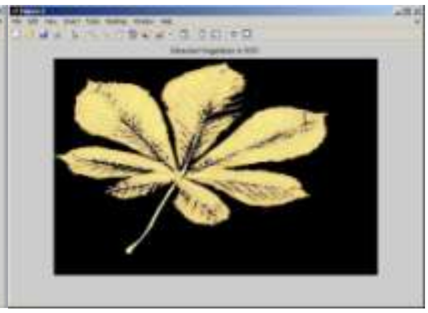


Figure 8.7.2: HSV Segmentation.

In the images below , the first column are the Original Image, second image column are the pictures of detected vegetation in RGB green priority technique and the last image column are the pictures of detected vegetation in HSV color space. In the images RGB technique detected some vegetation which could not be detect in HSV technique.


Figure 8.8.1: Original Image.


Figure 8.8.2: RGB Segmentation.


Figure 8.8.2: HSV Segmentation.

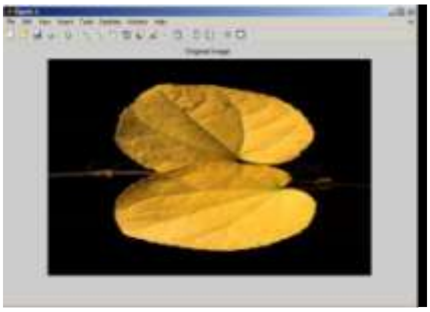


Figure 8.9.1: Original Image.

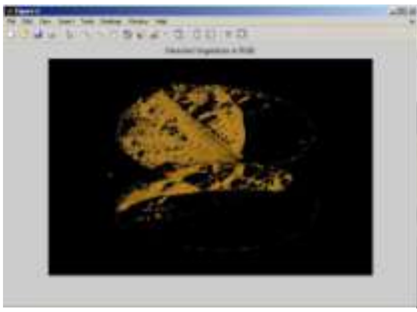


Figure 8.9.2: RGB Segmentation.

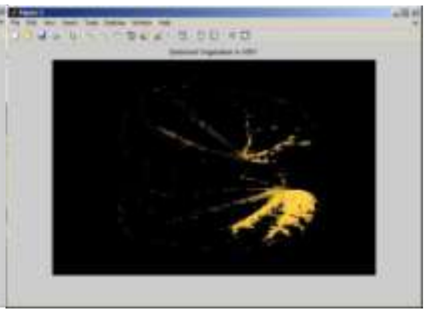


Figure 8.9.2: HSV Segmentation.


Figure 8.10.1: Original Image.


Figure 8.10.2: RGB Segmentation.


Figure 8.10.2: HSV Segmentation.


Figure 8.11.1: Original Image.


Figure 8.11.2: RGB Segmentation.


Figure 8.11.2: HSV Segmentation.

Figure 8.12.1: Original Image.

Figure 8.12.2: RGB Segmentation.

Figure 8.12.2: HSV Segmentation.

C.3 Experiment on the threshold for the Size Filter.

Different threshold values for the Size Filter and their corresponding outputs are given below

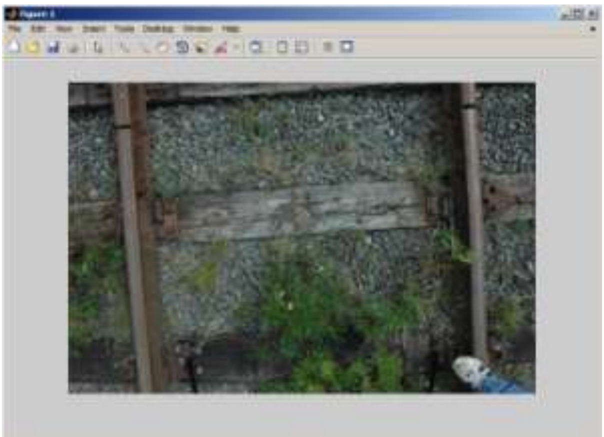


Figure 8.13: Original Image.

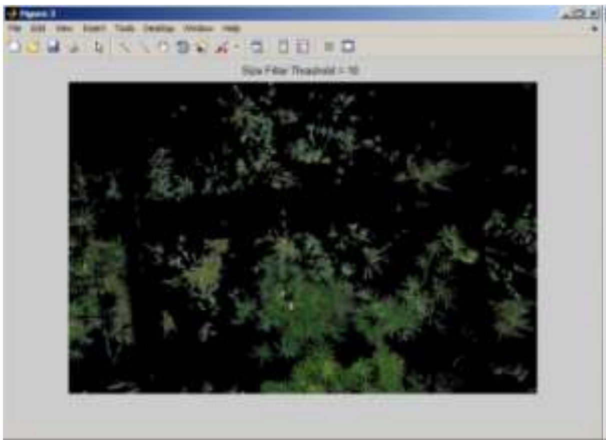
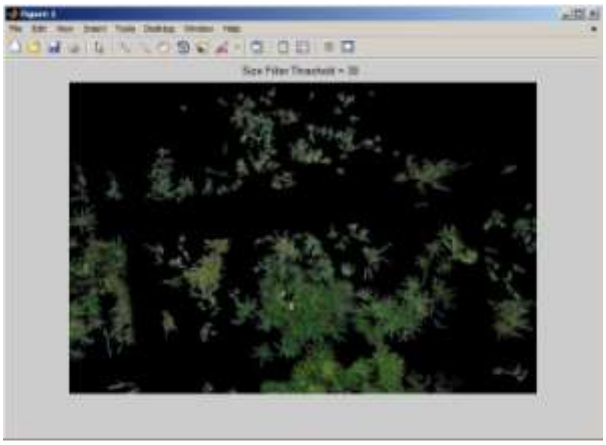


Figure 8.14.1: Total Vegetation after Size Filtering where Threshold =10.

Figure 8.14.2: Manmade objects after Size Filtering where Threshold =10.



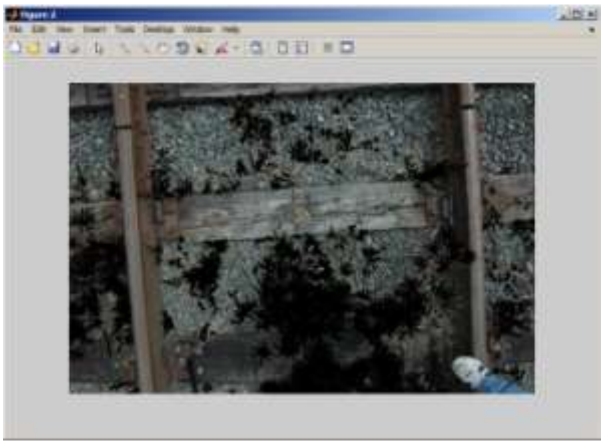


Figure 8.15.1: Total Vegetation after Size Filtering where Threshold =30.

Figure 8.15.2: Manmade objects after Size Filtering where Threshold =30.

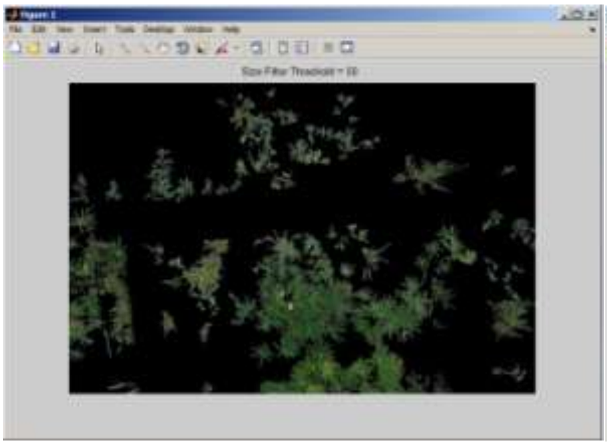


Figure 8.16.1: Total Vegetation after Size Filtering where Threshold =50.

Figure 8.16.2: Manmade objects after Size Filtering where Threshold =50.

Table 6: Some analysis of experiment for vegetation detection

Sample Image of manually assigned Vegetation regions	Total pixels of assigned vegetation regions (150×300 pixels)	Number of detected Vegetation pixels	Detection ratio = number of correctly detected pixels /total pixel of assigned regions (%)
	45000	38927	86.50**%**
	45000	43979	97.73**%**

	45000	40948	90.99**%**
	45000	43628	96.95**%**

	45000	38559	85.69**%**

False classification ratio was determined analogously. Some outputs are given below.

Table 7: Some analysis of experiment for false vegetation detection

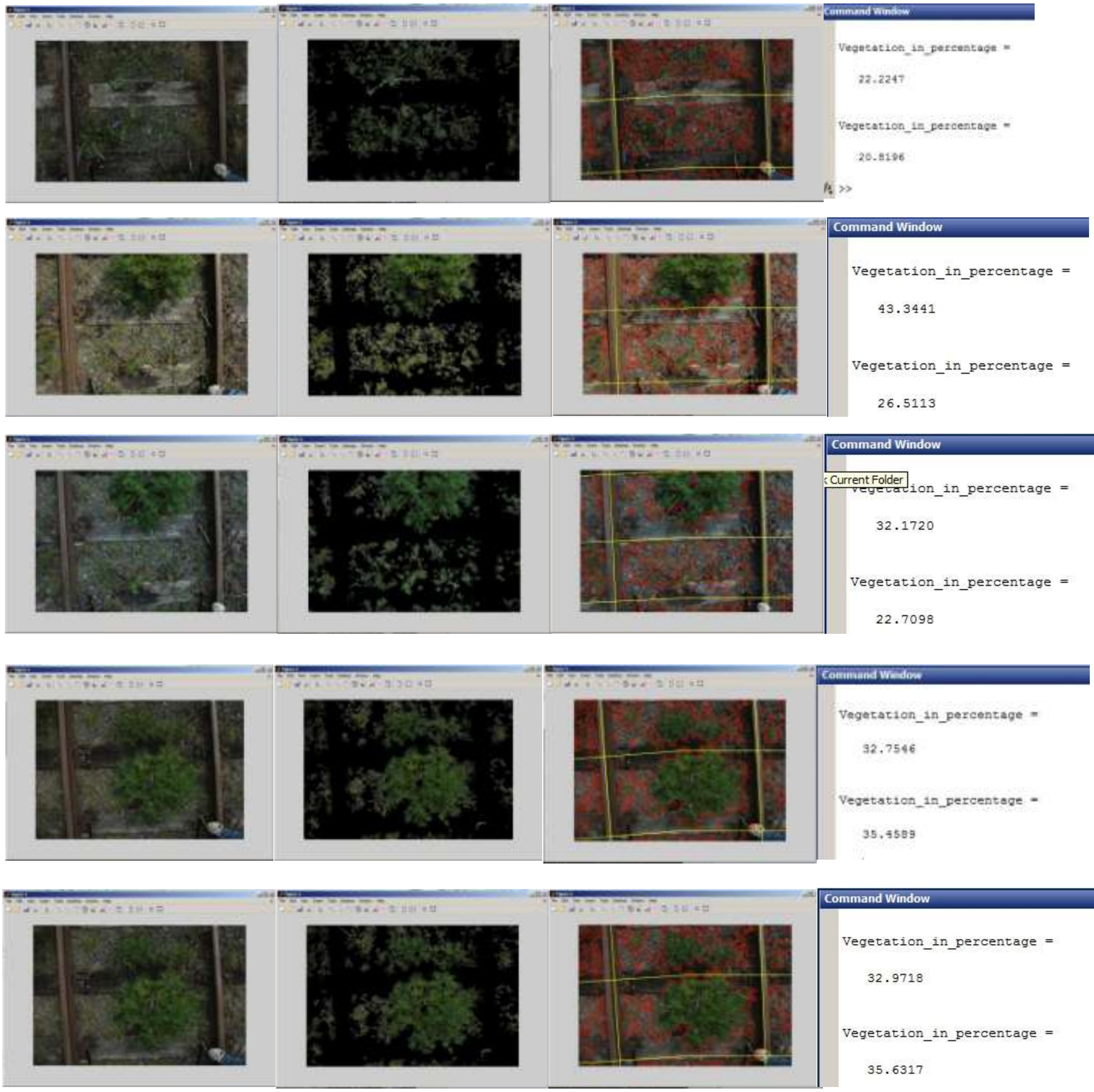
Sample Image of manually assigned Manmade objects regions	Total pixels of assigned manmade objects regions (150×300 pixels)	Number of falsely detected pixels as vegetation	False detection ratio (%)
	45000	295	0.65**%**

	45000	211	0.46%
	45000	466	1.03%

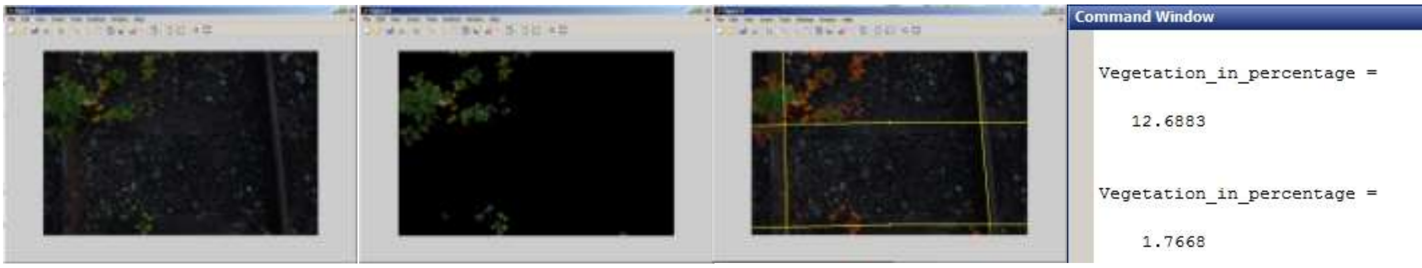
 	45000	32	0.07%
 	45000	132	0.29%

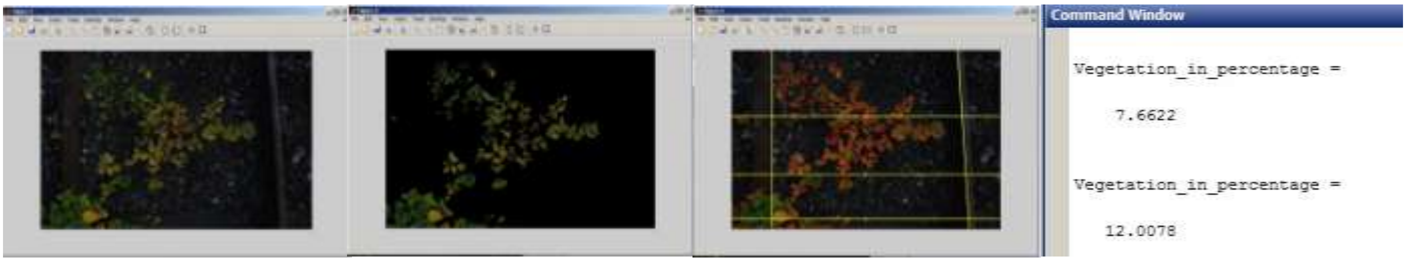
The average vegetation detection ratio is 90.87 % of the vegetated image regions. On an average only 0.43 % manmade object pixels are falsely classified as vegetation pixels.

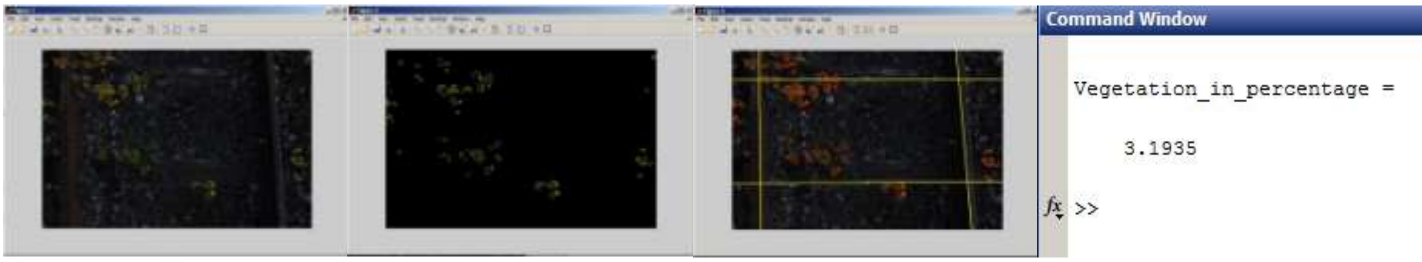
Outputs of our proposed system:

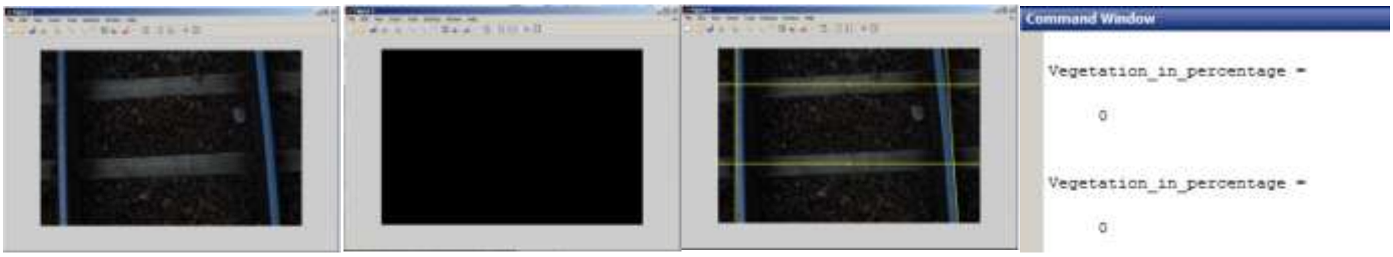


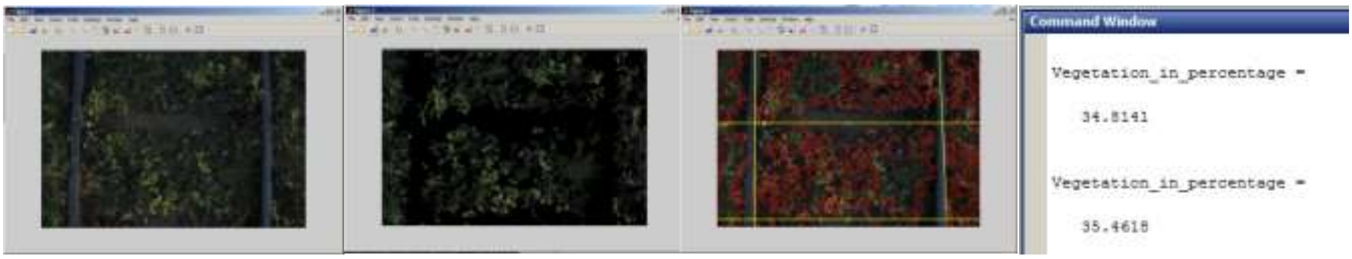

Command Window
Vegetation_in_percentage =
13.9195
Vegetation_in_percentage =
33.2563
Command Window
Vegetation_in_percentage =
10.5272
Vegetation_in_percentage =
29.7974
Command Window
Vegetation_in_percentage =
10.0238
Vegetation_in_percentage =
30.8021
Command Window
Vegetation_in_percentage =
0.4754
Vegetation_in_percentage =
0.2047
Command Window
Vegetation_in_percentage =
0.7489
Vegetation_in_percentage =
1.1380

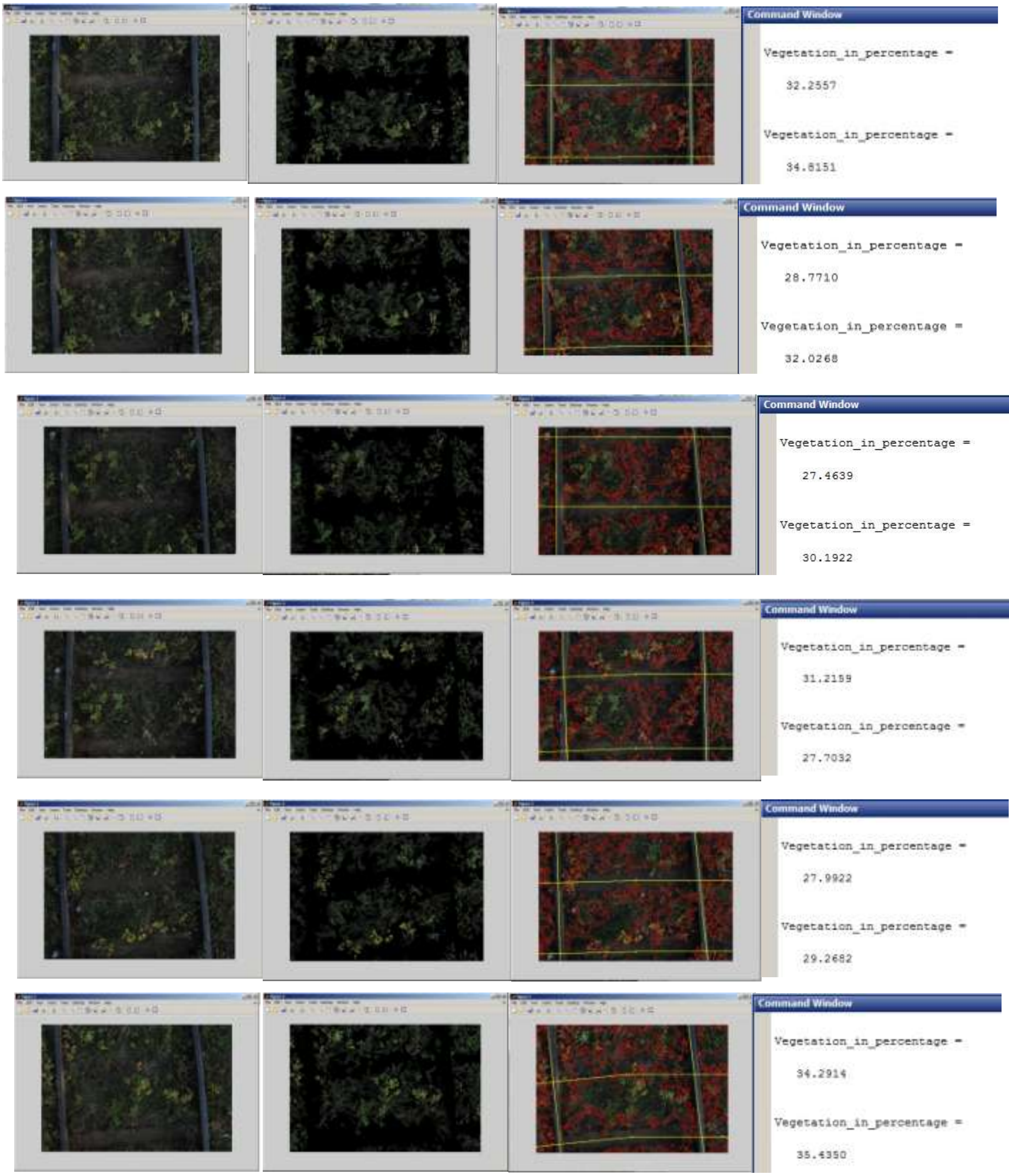

Command Window
Vegetation_in_percentage =
12.6883
Vegetation_in_percentage =
1.7668

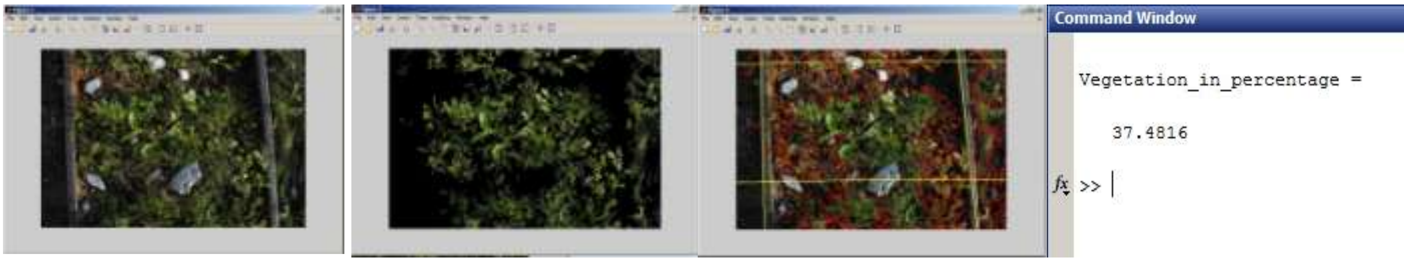

Command Window
Vegetation_in_percentage =
7.6622
Vegetation_in_percentage =
12.0078

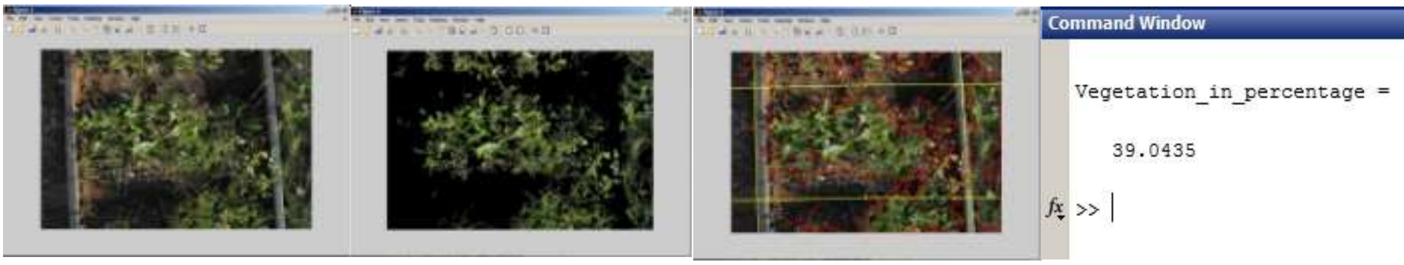

Command Window
Vegetation_in_percentage =
3.1935
fx >>

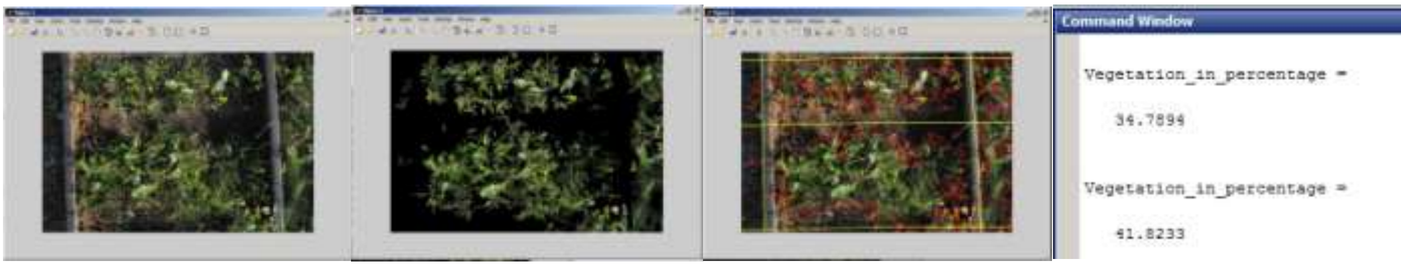

Command Window
Vegetation_in_percentage =
0
Vegetation_in_percentage =
0

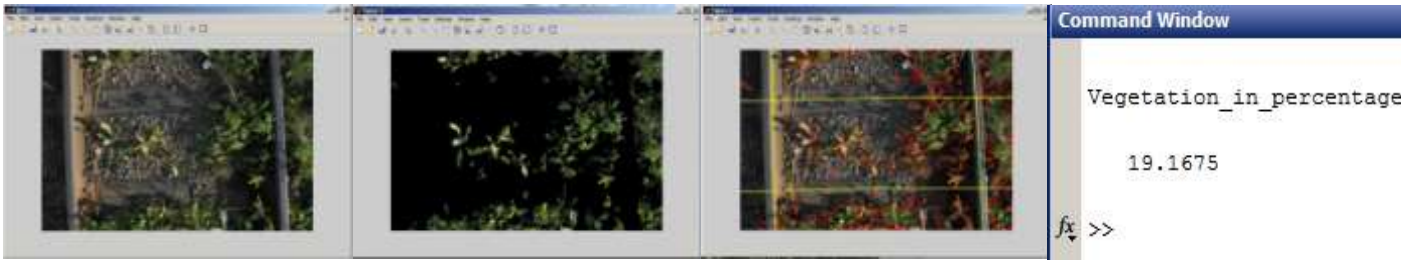

Command Window
Vegetation_in_percentage =
34.8141
Vegetation_in_percentage =
35.4618

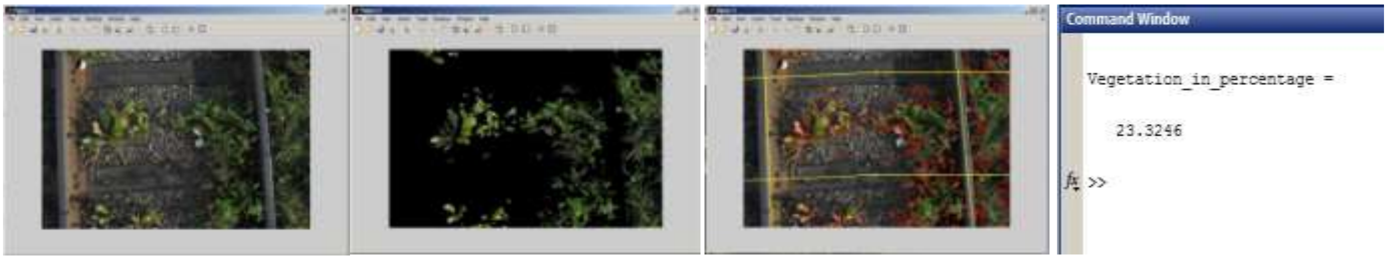

Command Window
Vegetation_in_percentage =
32.2557
Vegetation_in_percentage =
34.8151
Command Window
Vegetation_in_percentage =
28.7710
Vegetation_in_percentage =
32.0268
Command Window
Vegetation_in_percentage =
27.4639
Vegetation_in_percentage =
30.1922
Command Window
Vegetation_in_percentage =
31.2159
Vegetation_in_percentage =
27.7032
Command Window
Vegetation_in_percentage =
27.9922
Vegetation_in_percentage =
29.2682
Command Window
Vegetation_in_percentage =
34.2914
Vegetation_in_percentage =
35.4350

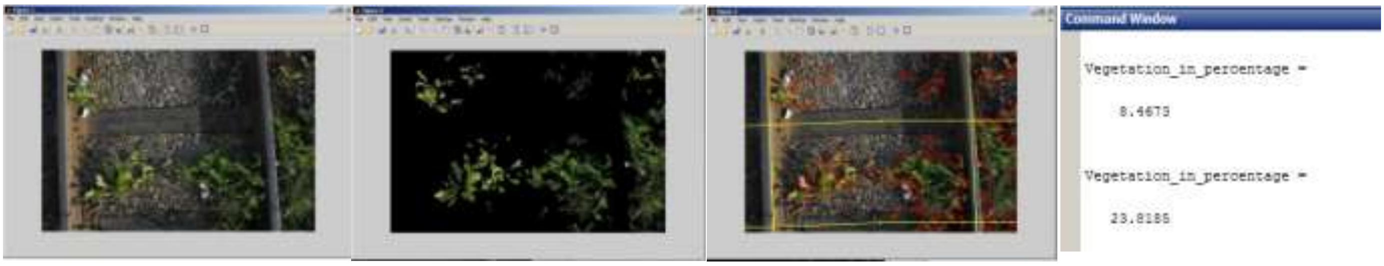

Command Window
Vegetation_in_percentage =
37.4816
>>

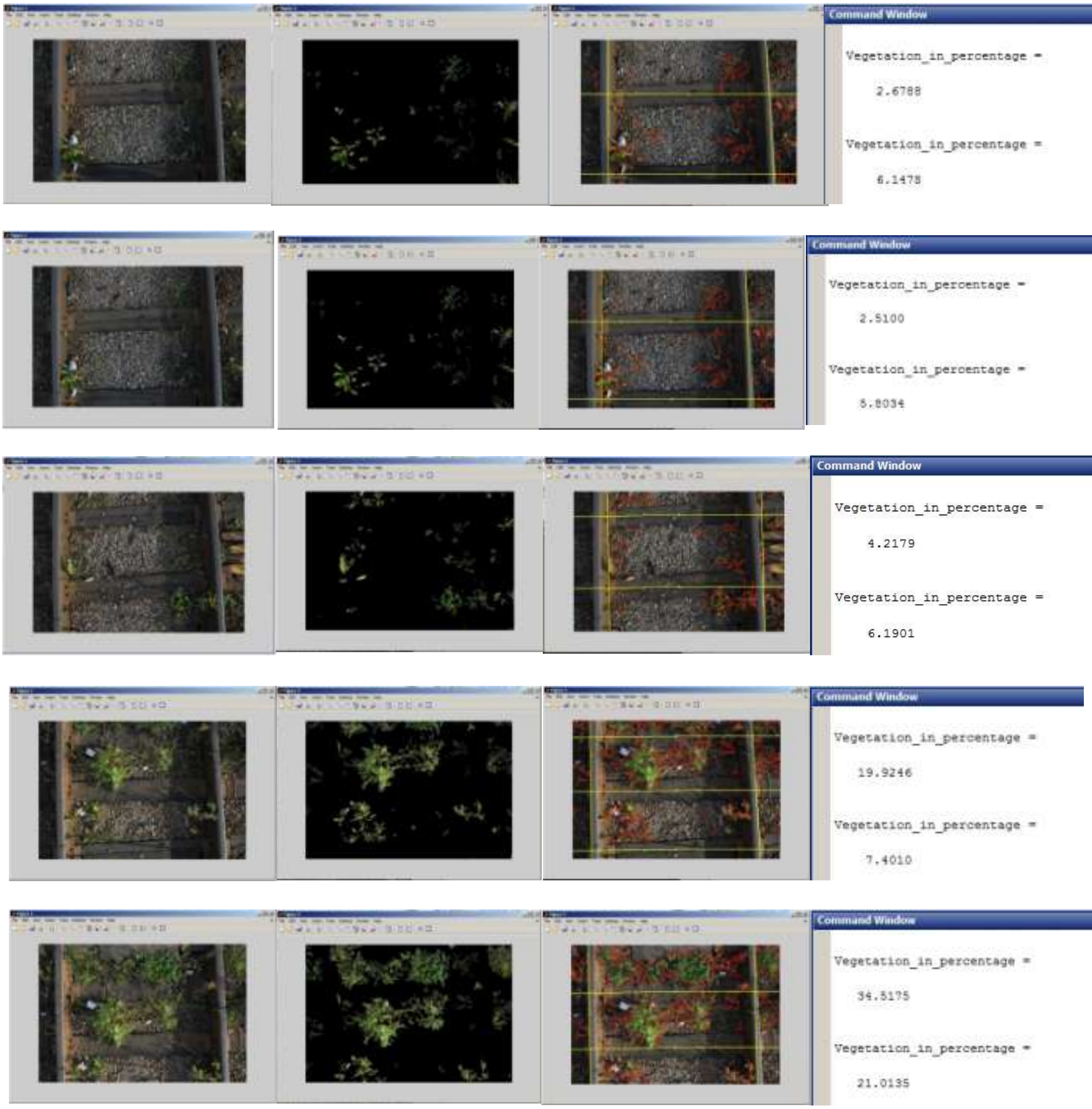

Command Window
Vegetation_in_percentage =
39.0435
>>


Command Window
Vegetation_in_percentage =
34.7894
Vegetation_in_percentage =
41.8233


Command Window
Vegetation_in_percentage
19.1675
>>


Command Window
Vegetation_in_percentage =
23.3246
>>


Command Window
Vegetation_in_percentage =
8.4673
Vegetation_in_percentage =
23.8185


Command Window
Vegetation_in_percentage =
2.6788
Vegetation_in_percentage =
6.1478
Command Window
Vegetation_in_percentage =
2.5100
Vegetation_in_percentage =
5.8034
Command Window
Vegetation_in_percentage =
4.2179
Vegetation_in_percentage =
6.1901
Command Window
Vegetation_in_percentage =
19.9246
Vegetation_in_percentage =
7.4010
Command Window
Vegetation_in_percentage =
34.5175
Vegetation_in_percentage =
21.0135

Outputs on different types of images by vegetation detection part